2550 Intro to cybersecurity

L14: Anonymous data isn't!

abhi shelat

Thanks to Ran Cohen for help with slides.

The era of big data

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Predict our preferences

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Social networks

facebook

flickr

twitter

Pinterest

reddit

Instagram

LinkedIn

myspace

Social networks

facebook

flickr

twitter

Pinterest

reddit

Instagram

LinkedIn

myspace

Medical & Genomic data

23andMe

wellcome sanger institute

patientslikeme®

deCODE genetics

CERNER® All Together™

BROAD INSTITUTE

Medical & Genomic data

Contact tracing

Statistical data

United States™
Census
Bureau

Statistical data

Big Data is Invaluable

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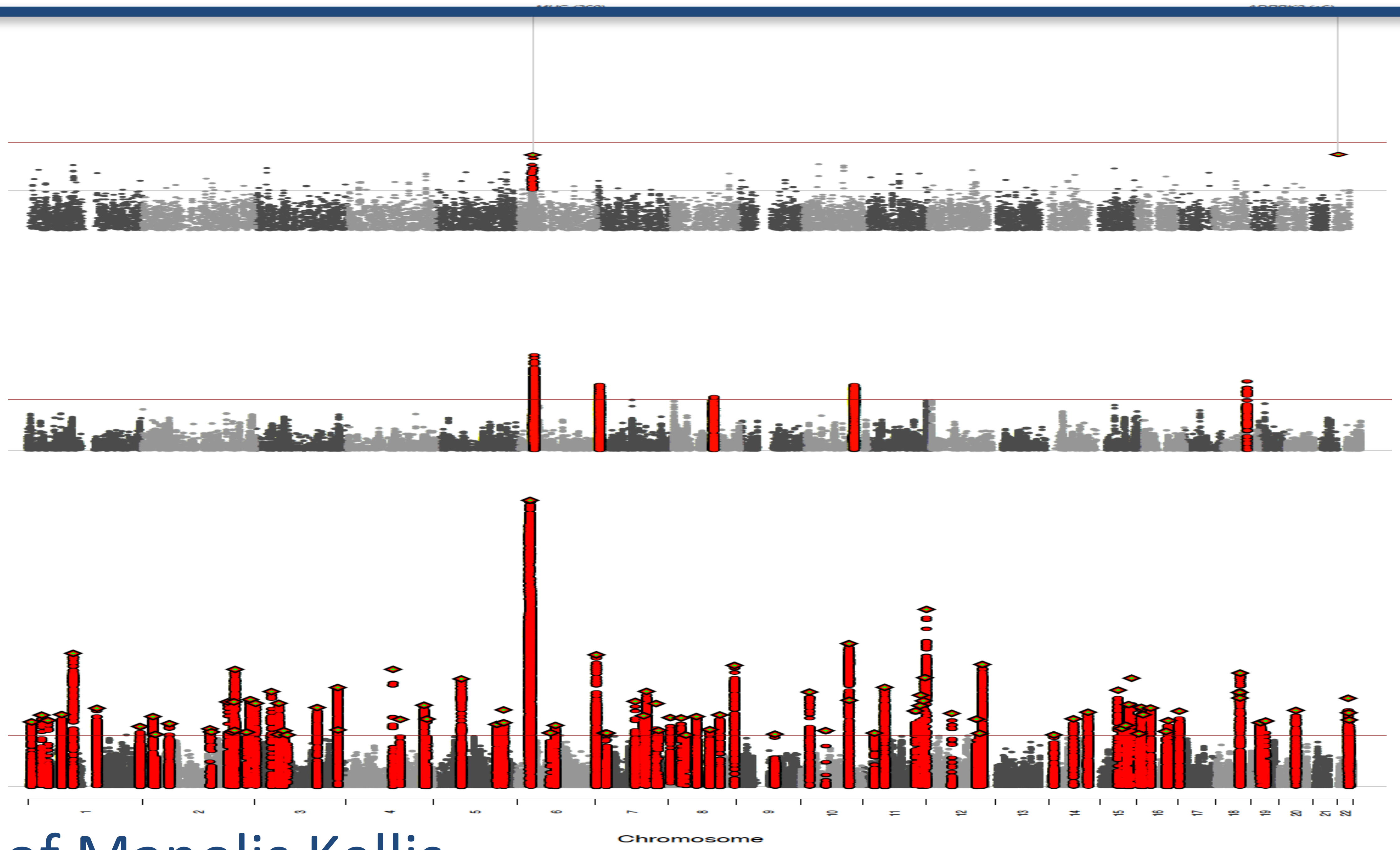
Schizophrenia Genome-Wide Association Studies

3,500 cases ⇔ 0 loci

10,000 cases ⇔ 5 loci

35,000 cases ⇔ 62 loci!



Data courtesy of Manolis Kellis

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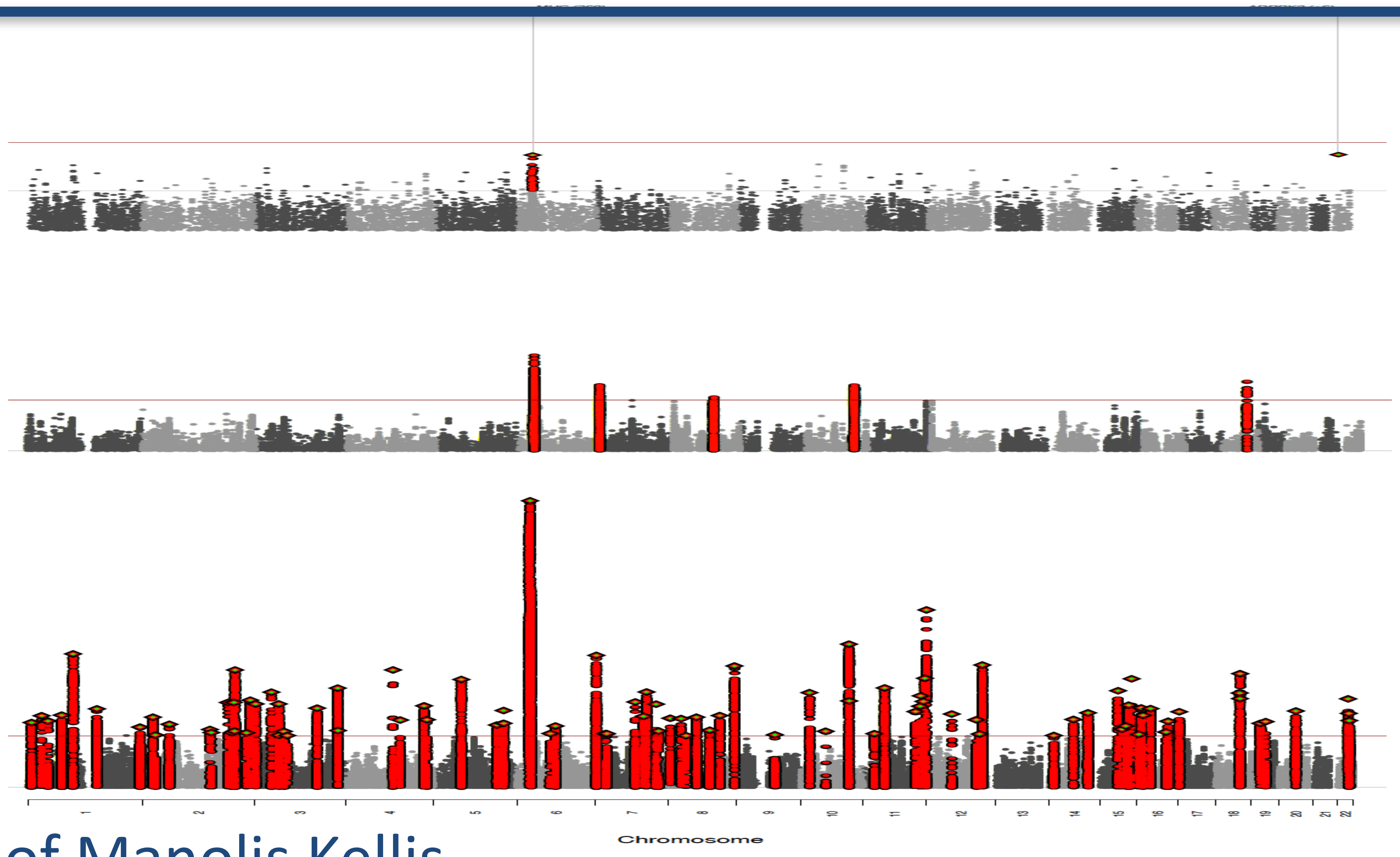

Data courtesy of Manolis Kellis

Increasing sample sizes for schizophrenia association studies has led to increases in the number of risk genes discovered

new biological insights

Security tradeoff

How can we benefit from the unpredictable advances that big data may provide, while maintaining high standards of privacy for the data contributors?

Outline

- Popular ideas that do not work
  + privacy horror stories
- An approach that works

Popular idea #1

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Remove Personally Identifiable Information (PII)

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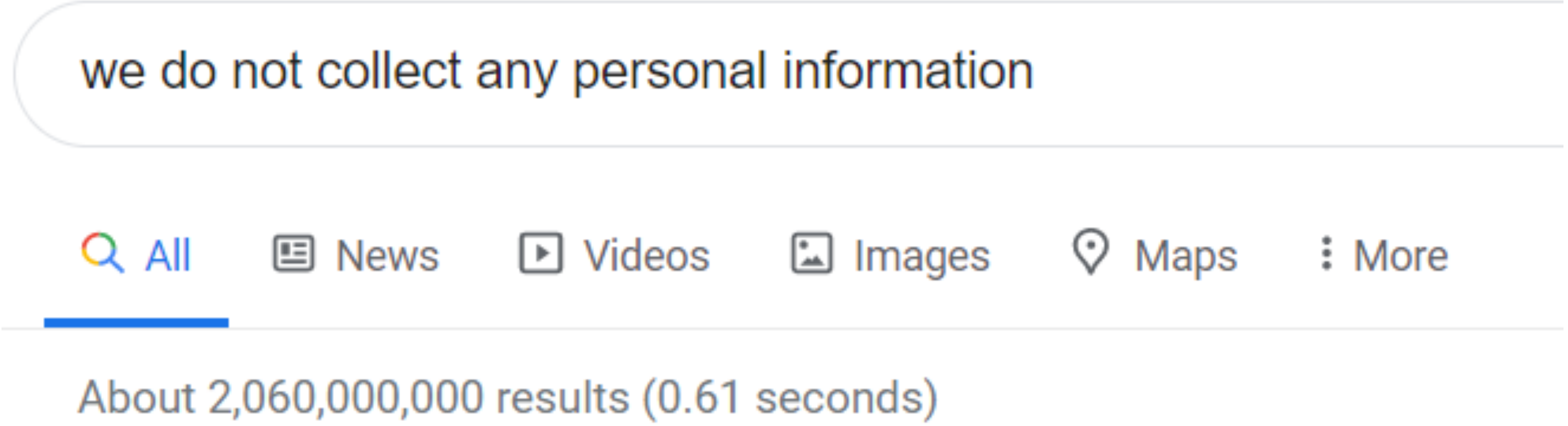

Anonymizing data

NIST

National Institute of
Standards and Technology
U.S. Department of Commerce

Special Publication 800-122

Guide to Protecting the Confidentiality of Personally Identifiable Information (PII)

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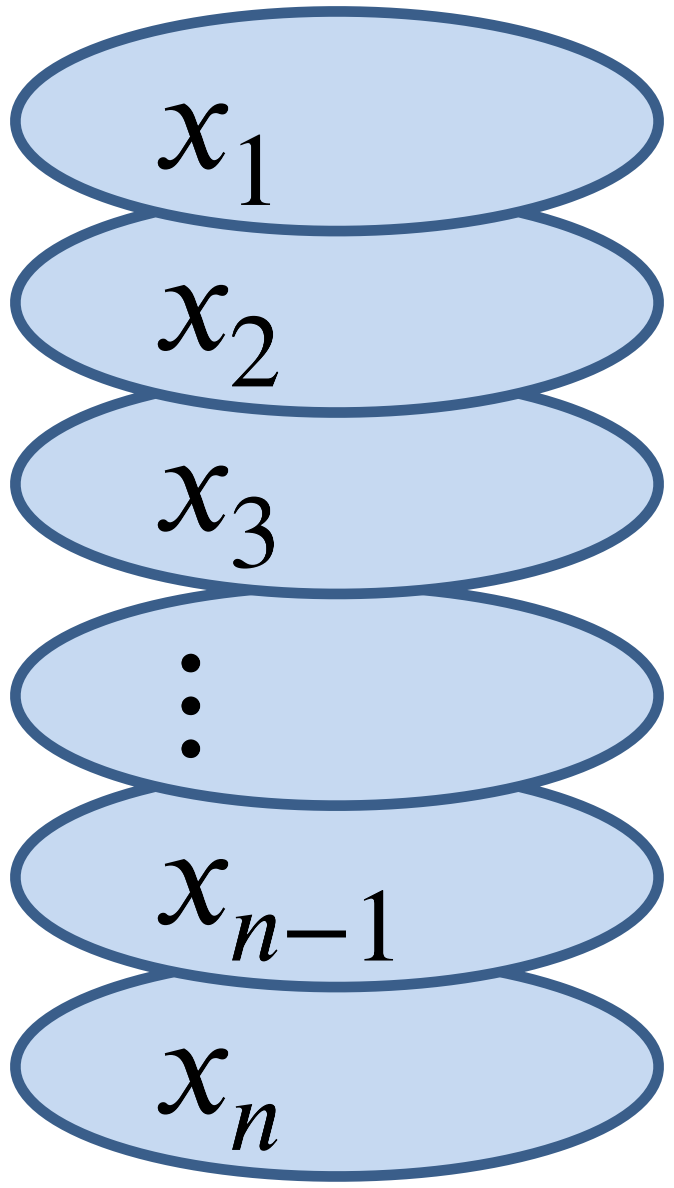

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(n records of
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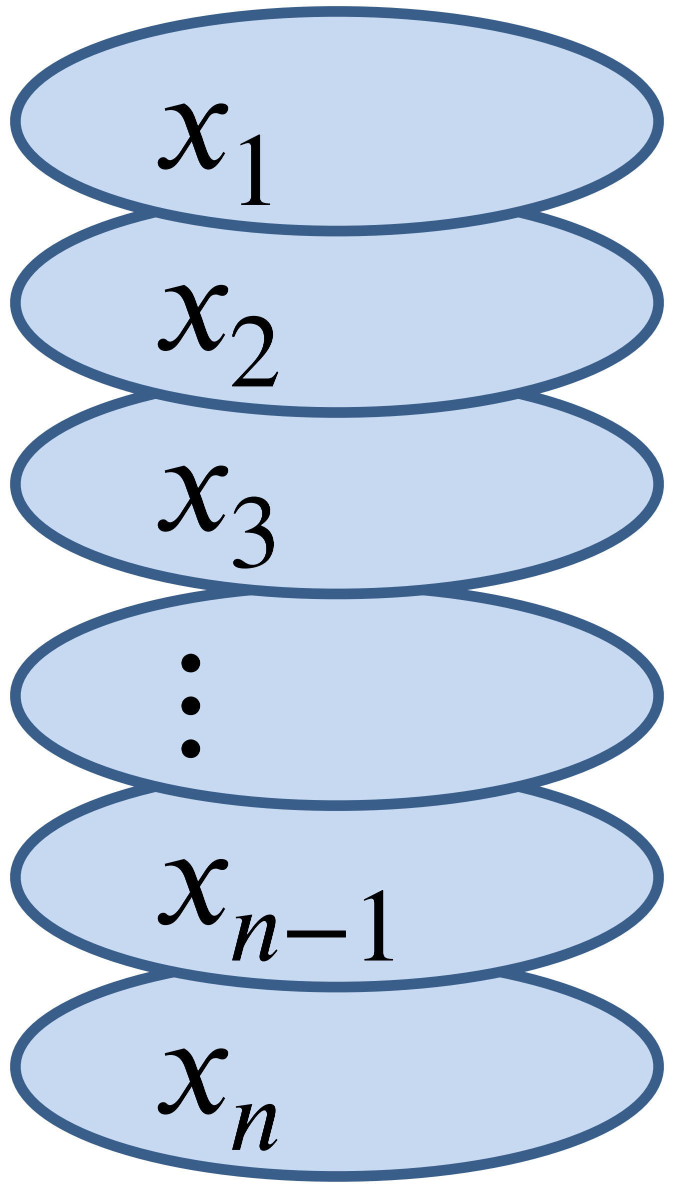

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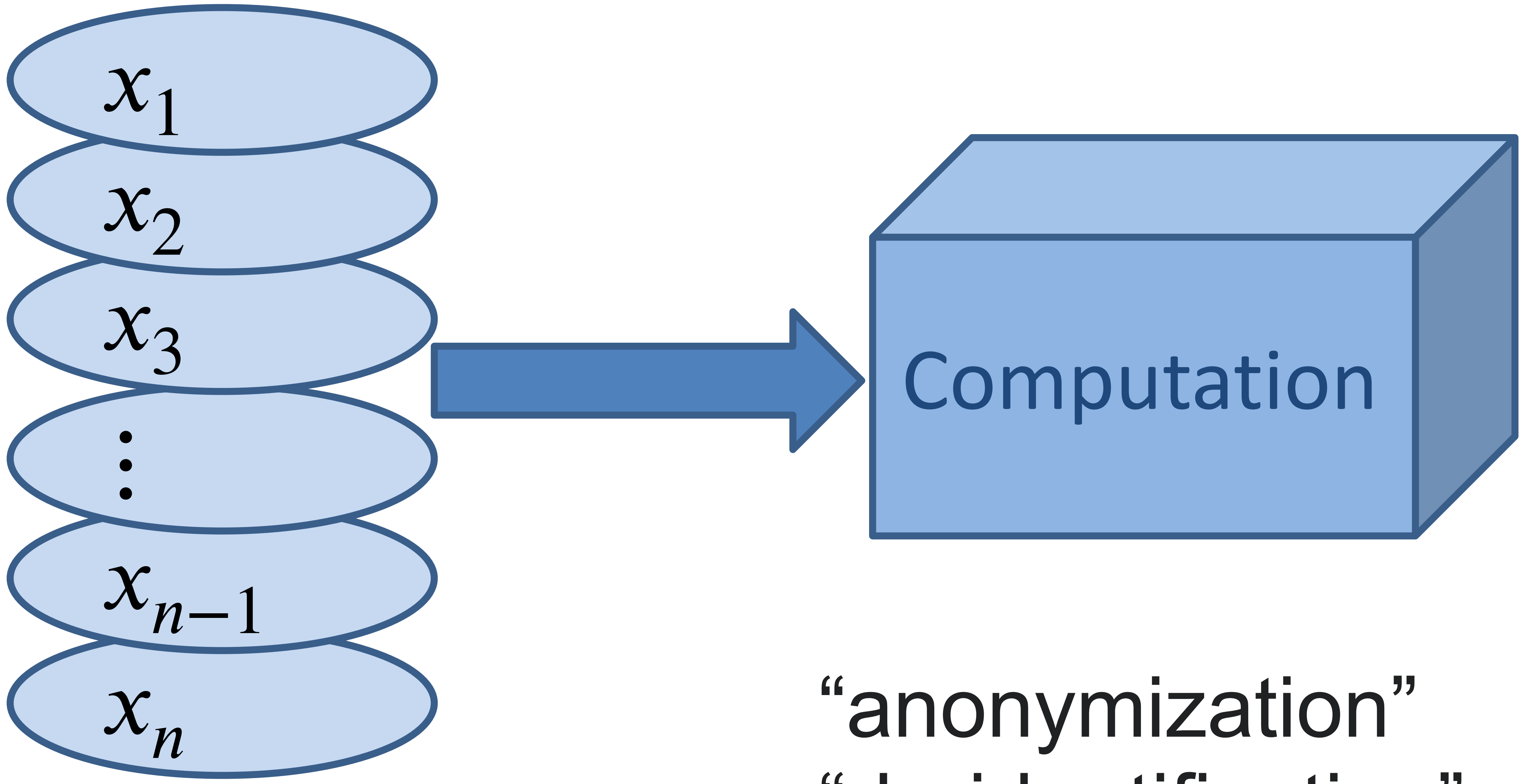

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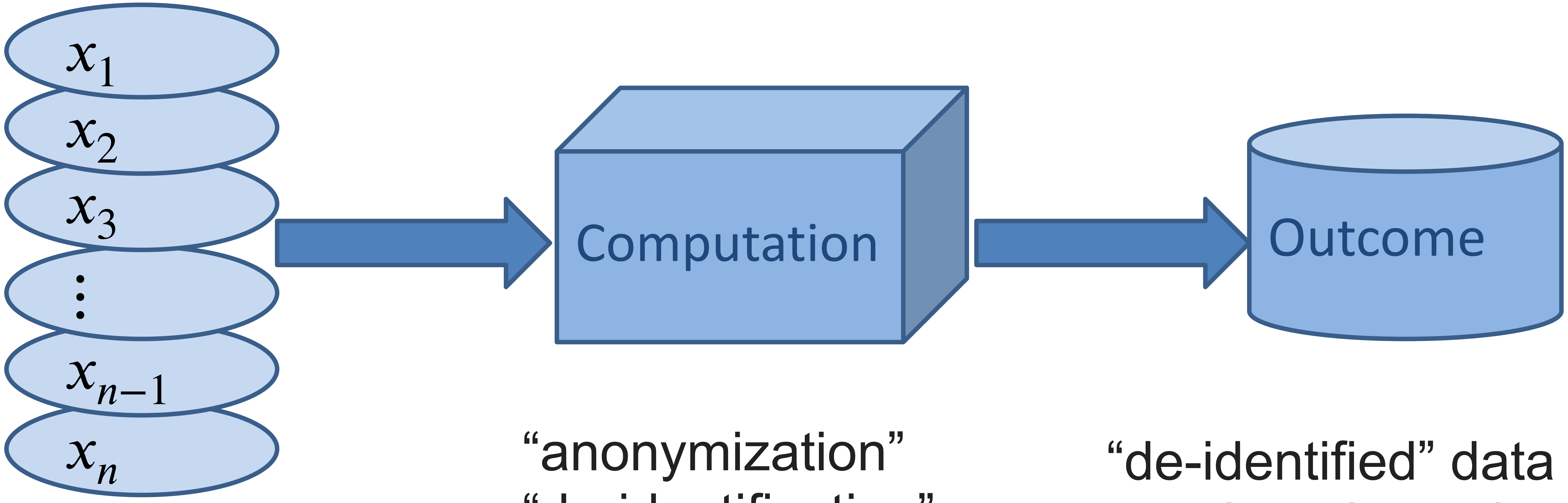

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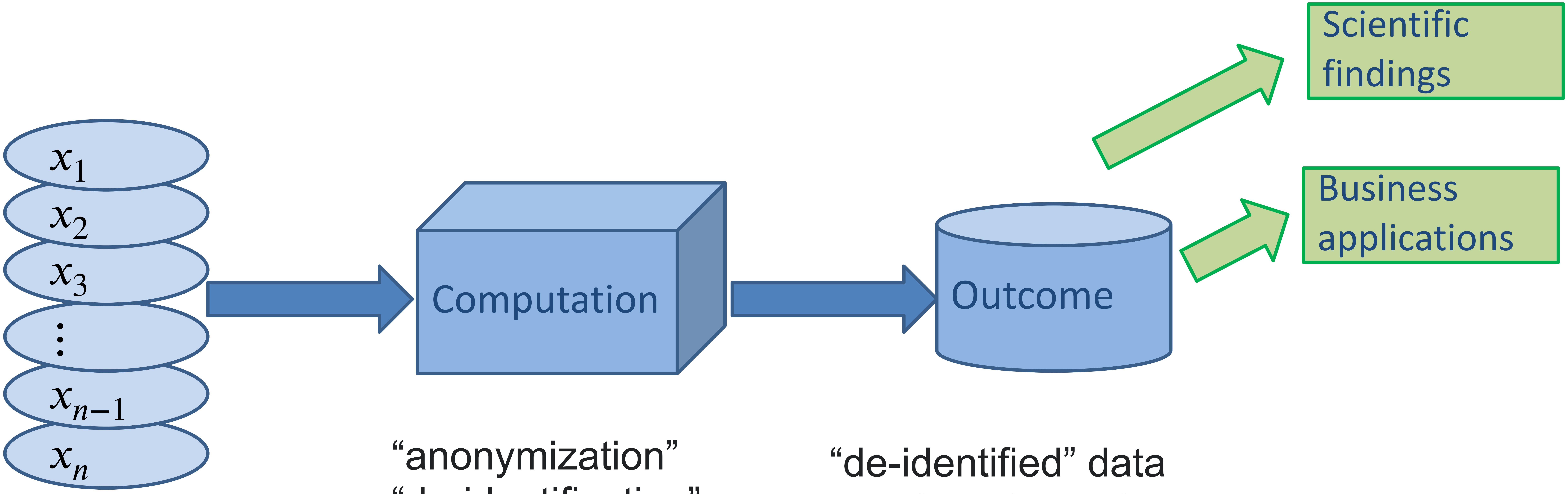

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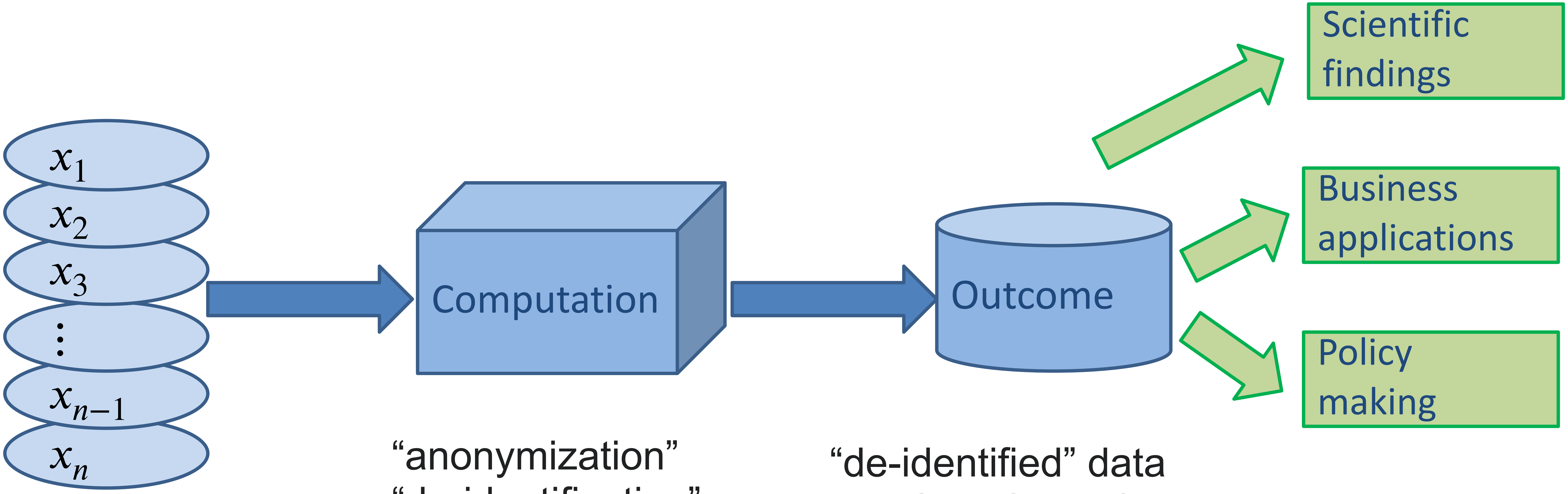

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- William Weld, then Governor of Massachusetts, assured the public that GIC had protected patient privacy by deleting identifiers

Linkage attack (Sweeney ‘97)

MA Group Insurance Commission

- Contained ~135,000 patients
- Anonymized: Name, SSN removed

Ethnicity
Visit date
Diagnosis
Procedure
Medication
Total charge

Date of Birth
ZIP
Sex

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Voters registration of Cambridge MA

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Address
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Party affiliation
Date last voted

Register to VOTE

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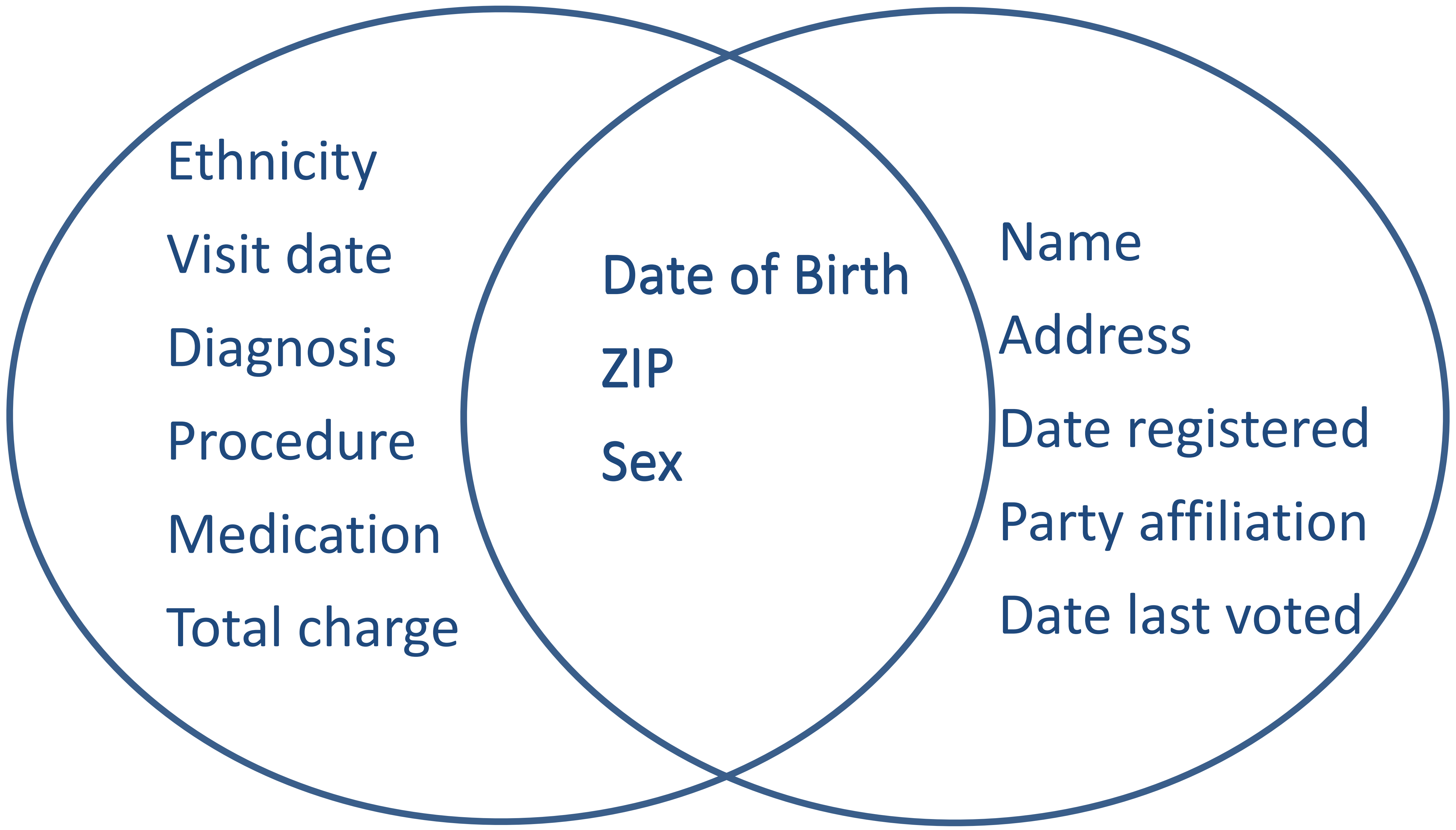

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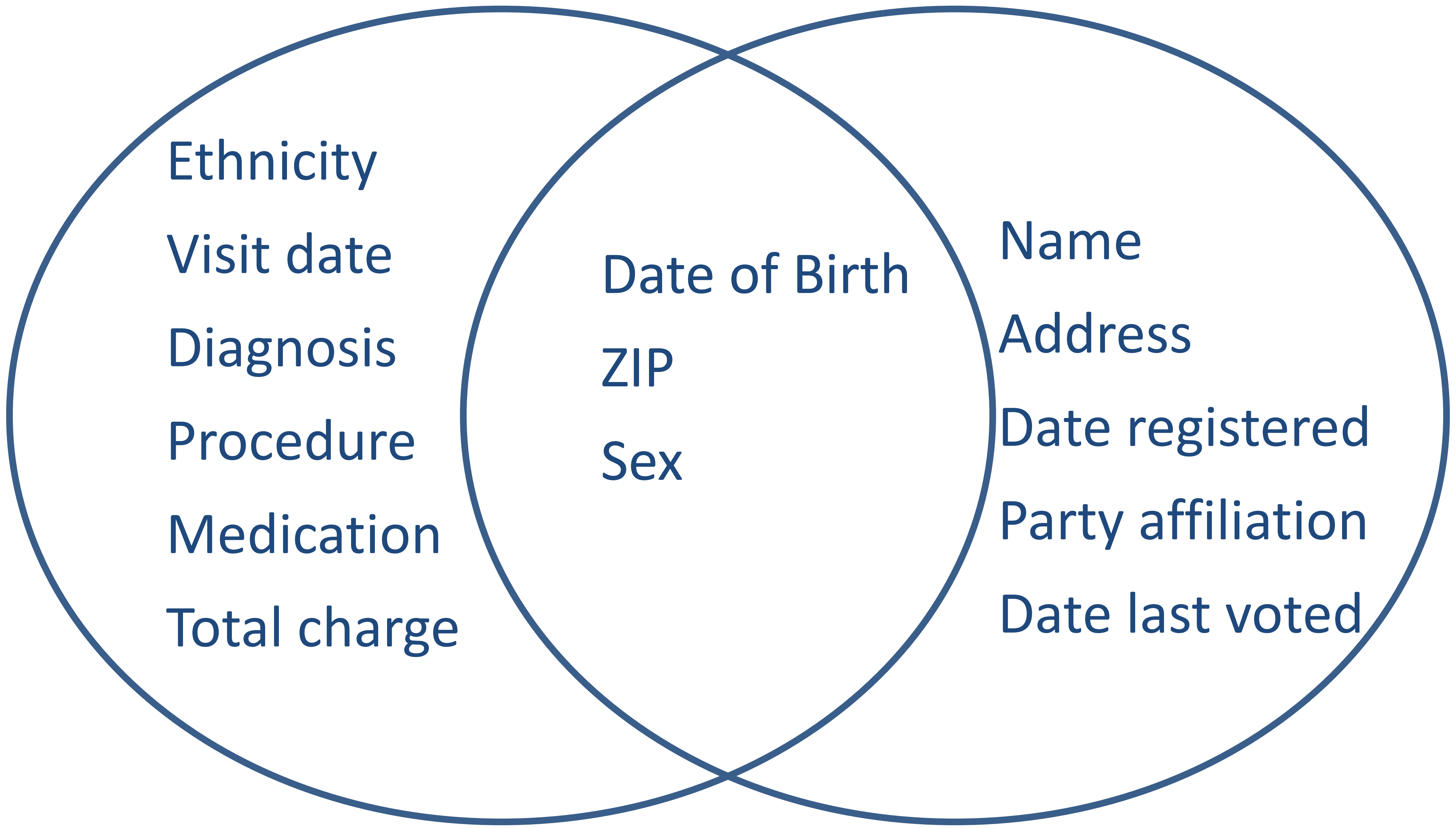

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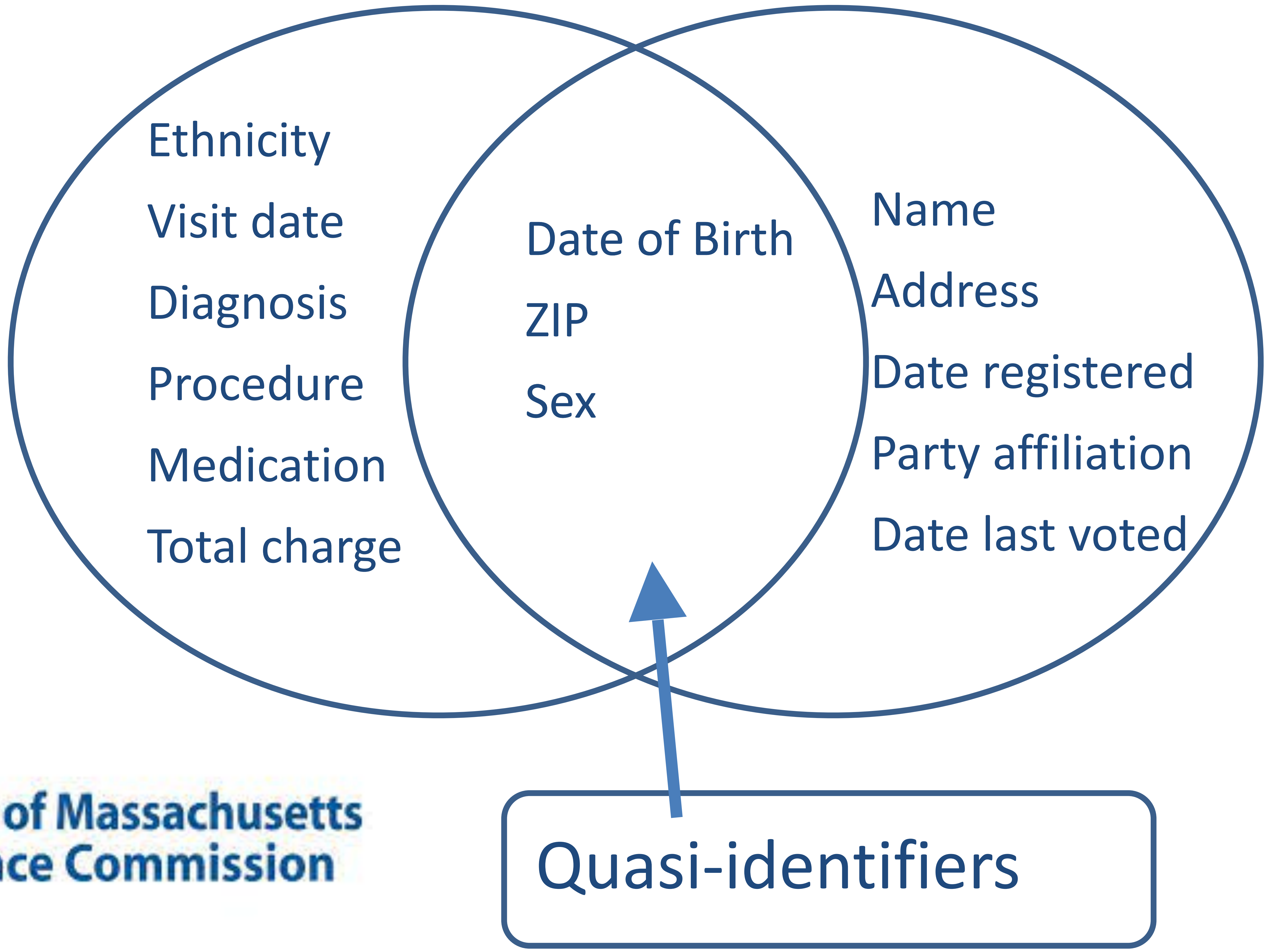

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- (DoB, ZIP, Sex) uniquely identifies 87% of US population
- Re-identified medical records of William Weld (MA governor at the time)
- In Cambridge voters list
  - Six people shared his DoB
  - Three of which were men
  - He was the only one in his ZIP code
- Significant impact on privacy policymaking and the health privacy legislation HIPAA (Health Insurance Portability and Accountability Act)

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4417749best dog for older owner	3/6/2006	11:48:24	1	http://www.canismajor.com
4417749best dog for older owner	3/6/2006	11:48:24	5	http://dogs.about.com
4417749landscapers in lilburn ga.	3/6/2006	18:37:26		
4417749 effects of nicotine	3/7/2006	19:17:19	6	http://www.nida.nih.gov
4417749best retirement in the world	3/9/2006	21:47:26	4	http://www.escapeartist.com
4417749best retirement place in usa	3/9/2006	21:49:37	10	http://www.clubmarena.com
4417749best retirement place in usa	3/9/2006	21:49:37	9	http://www.committment.com
4417749bi polar and heredity	3/13/2006	20:57:11		
4417749adventure for the older american	3/17/2006	21:35:48		
4417749nicotine effects on the body	3/26/2006	10:31:15	3	http://www.geocities.com
4417749nicotine effects on the body	3/26/2006	10:31:15	2	http://health.howstuffworks.com
4417749wrinkling of the skin	3/26/2006	10:38:23		
4417749mini strokes	3/26/2006	14:56:56	1	http://www.ninds.nih.gov
4417749panic disorders	3/26/2006	14:58:25		
4417749jarrett t. arnold eugene oregon	3/23/2006	21:48:01	2	http://www2.eugeneweekly.com
4417749jarrett t. arnold eugene oregon	3/23/2006	21:48:01	3	http://www2.eugeneweekly.com
4417749plastic surgeons in gwinnett county	3/28/2006	15:04:23	1	http://www.wedalert.com
4417749plastic surgeons in gwinnett county	3/28/2006	15:04:23	4	http://www.implantinfo.com
4417749plastic surgeons in gwinnett county	3/28/2006	15:31:00		
441774960 single men	3/29/2006	20:11:52	6	http://www.adultlovecompass.com
441774960 single men	3/29/2006	20:14:14		
4417749clothes for 60 plus age	4/19/2006	12:44:03		
4417749clothes for age 60	4/19/2006	12:44:41	10	http://www.news.cornell.edu
4417749clothes for age 60	4/19/2006	12:45:41		
4417749lactose intolerant	4/21/2006	20:53:51	2	http://digestive.niddk.nih.gov
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4417749nicotine effects on the body	3/26/2006	10:31:15	3	http://www.geocities.com
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4417749wrinkling of the skin	3/26/2006	10:38:23		
4417749mini strokes	3/26/2006	14:56:56	1	http://www.ninds.nih.gov
4417749panic disorders	3/26/2006	14:58:25		
4417749jarrett t. arnold eugene oregon	3/23/2006	21:48:01	2	http://www2.eugeneweekly.com
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441774960 single men	3/29/2006	20:11:52	6	http://www.adultlovecompass.com
441774960 single men	3/29/2006	20:14:14		
4417749clothes for 60 plus age	4/19/2006	12:44:03		
4417749clothes for age 60	4/19/2006	12:44:41	10	http://www.news.cornell.edu
4417749clothes for age 60	4/19/2006	12:45:41		
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Data itself leaks PII

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- Prize won by Bellkore’s Pragmatic Chaos team, 2009

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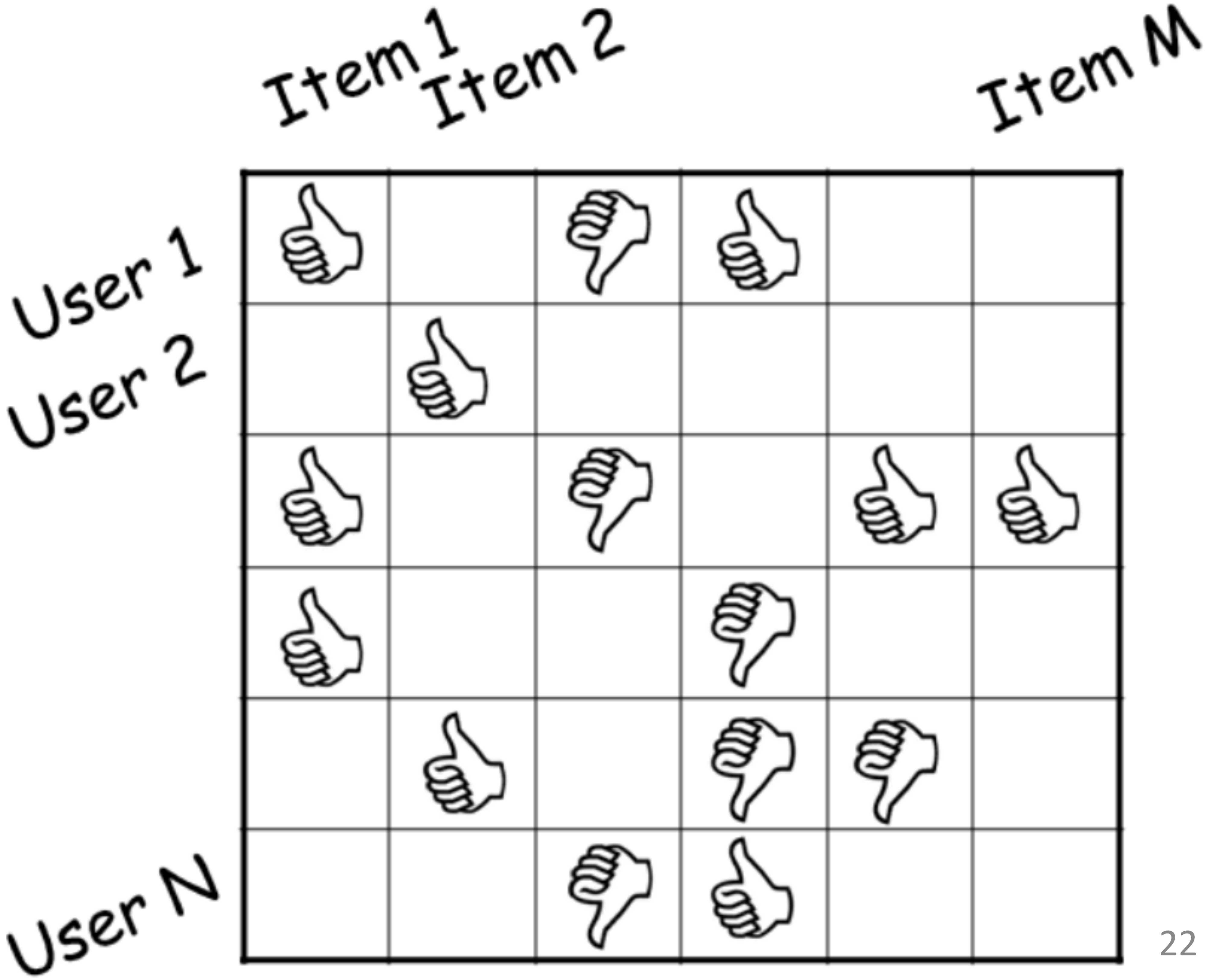

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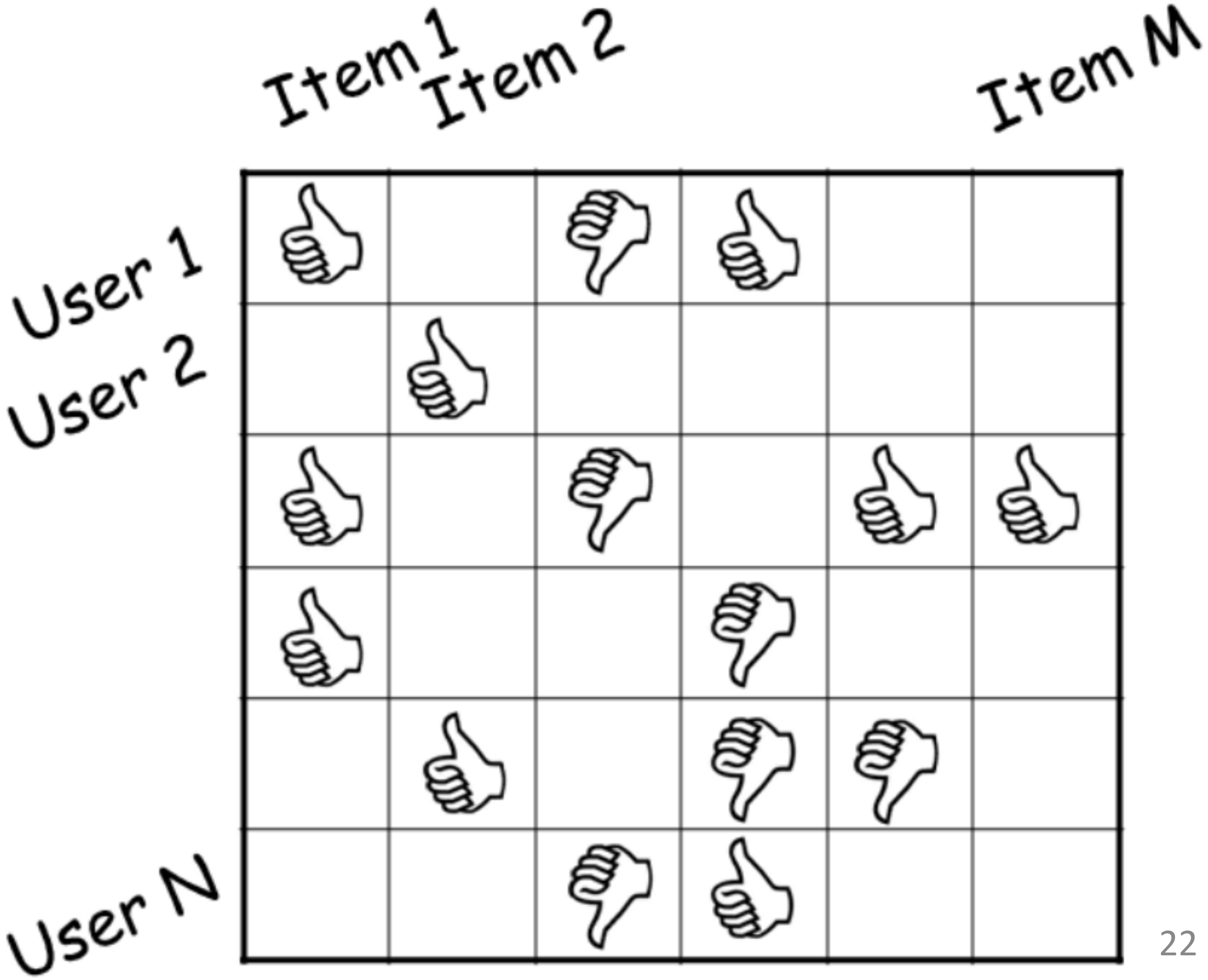

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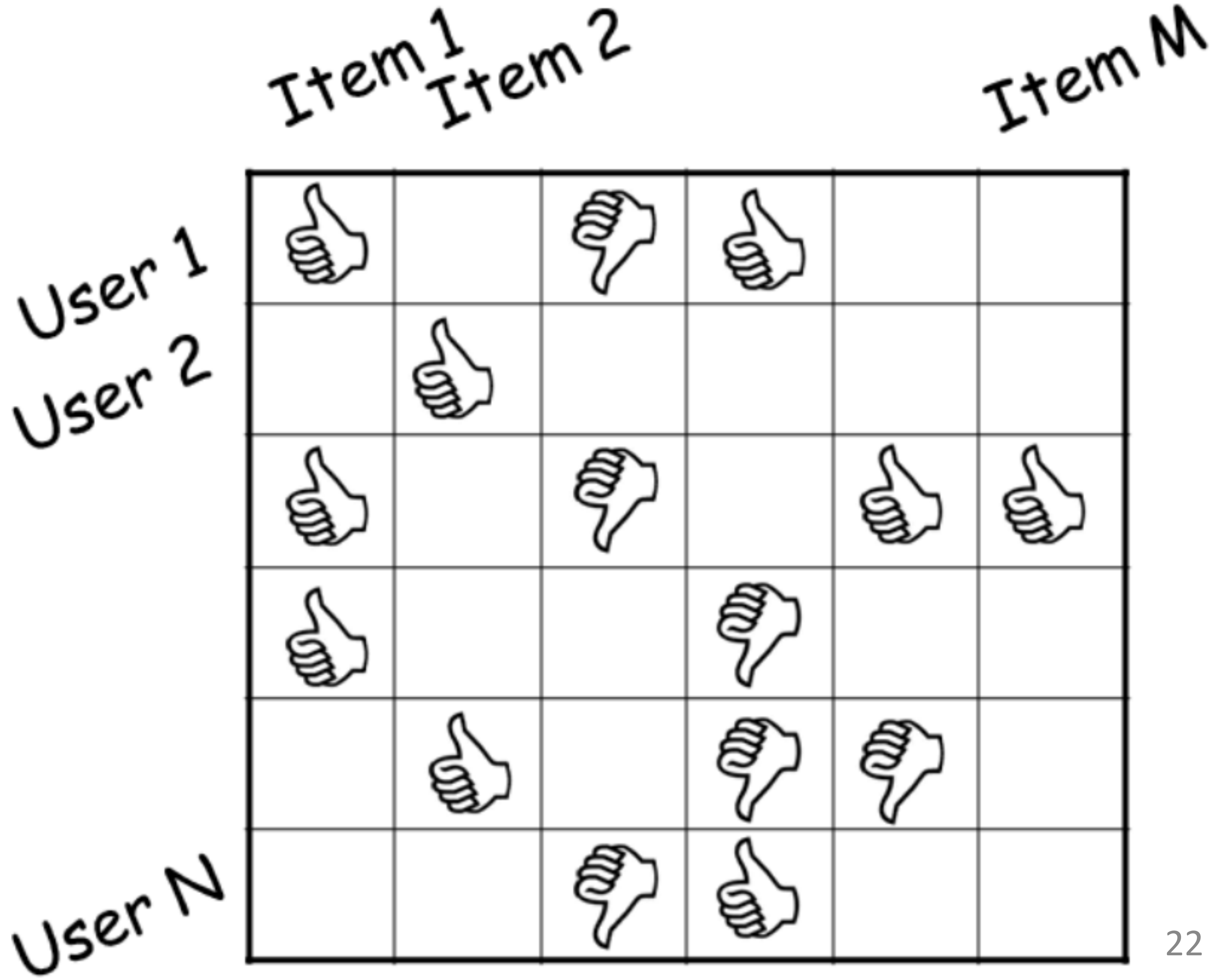
- Narayanan and Shmatikov re-identified the data



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IMDb Datasets

Subsets of IMDb data are available for access to customers for personal and non-commercial use. You can hold local copies of this data, and it is subject to our terms and conditions. Please refer to the Non-Commercial Licensing and copyright/license and verify compliance.

Data Location

The dataset files can be accessed and downloaded from https://datasets.imdbws.com/. The data is refreshed daily.

IMDb Dataset Details

Each dataset is contained in a gzipped, tab-separated-values (TSV) formatted file in the UTF-8 character set. The first line in each file contains headers that describe what is in each column. A '\N' is used to denote that a particular field is missing or null for that title/name. The available datasets are as follows:

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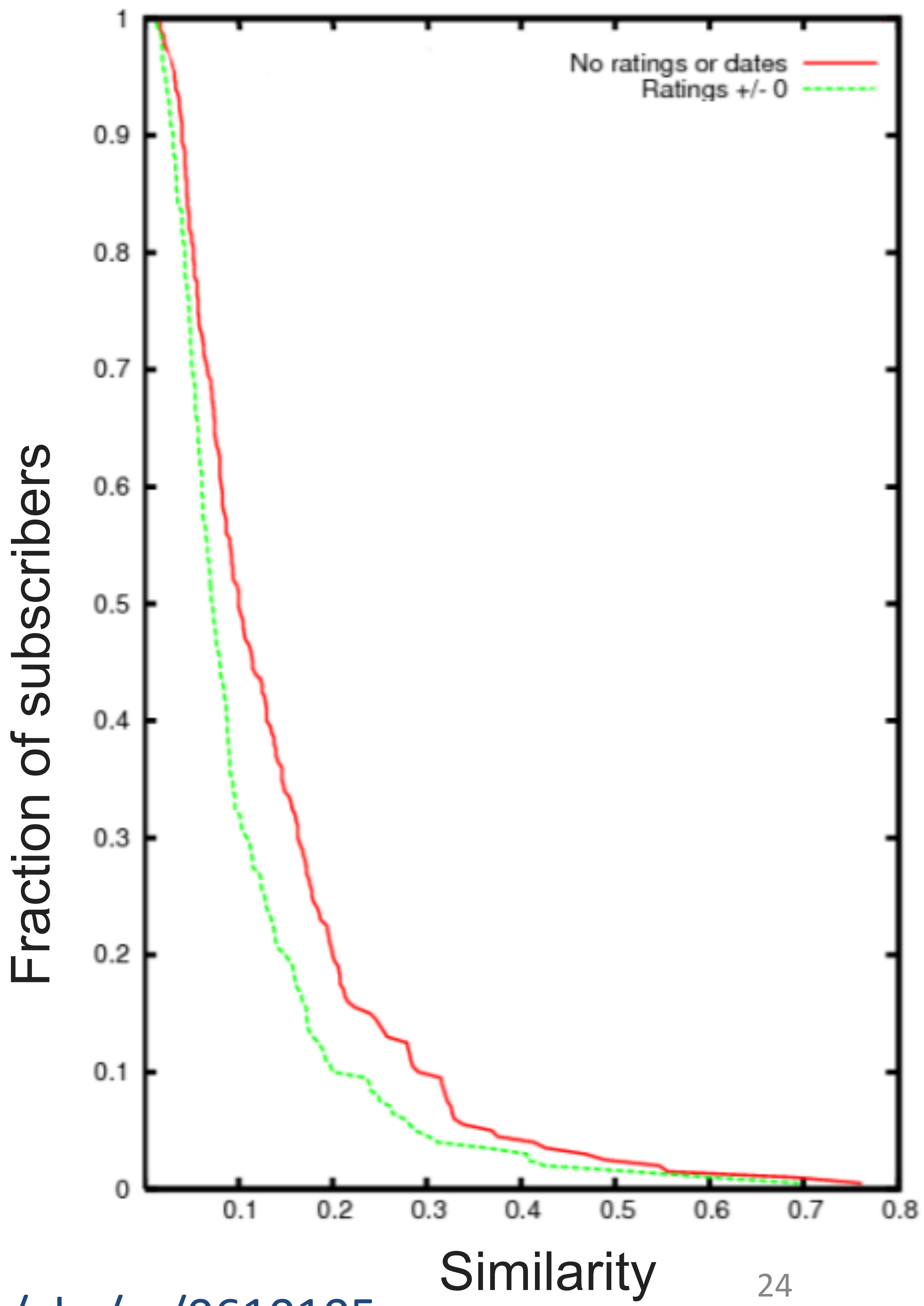

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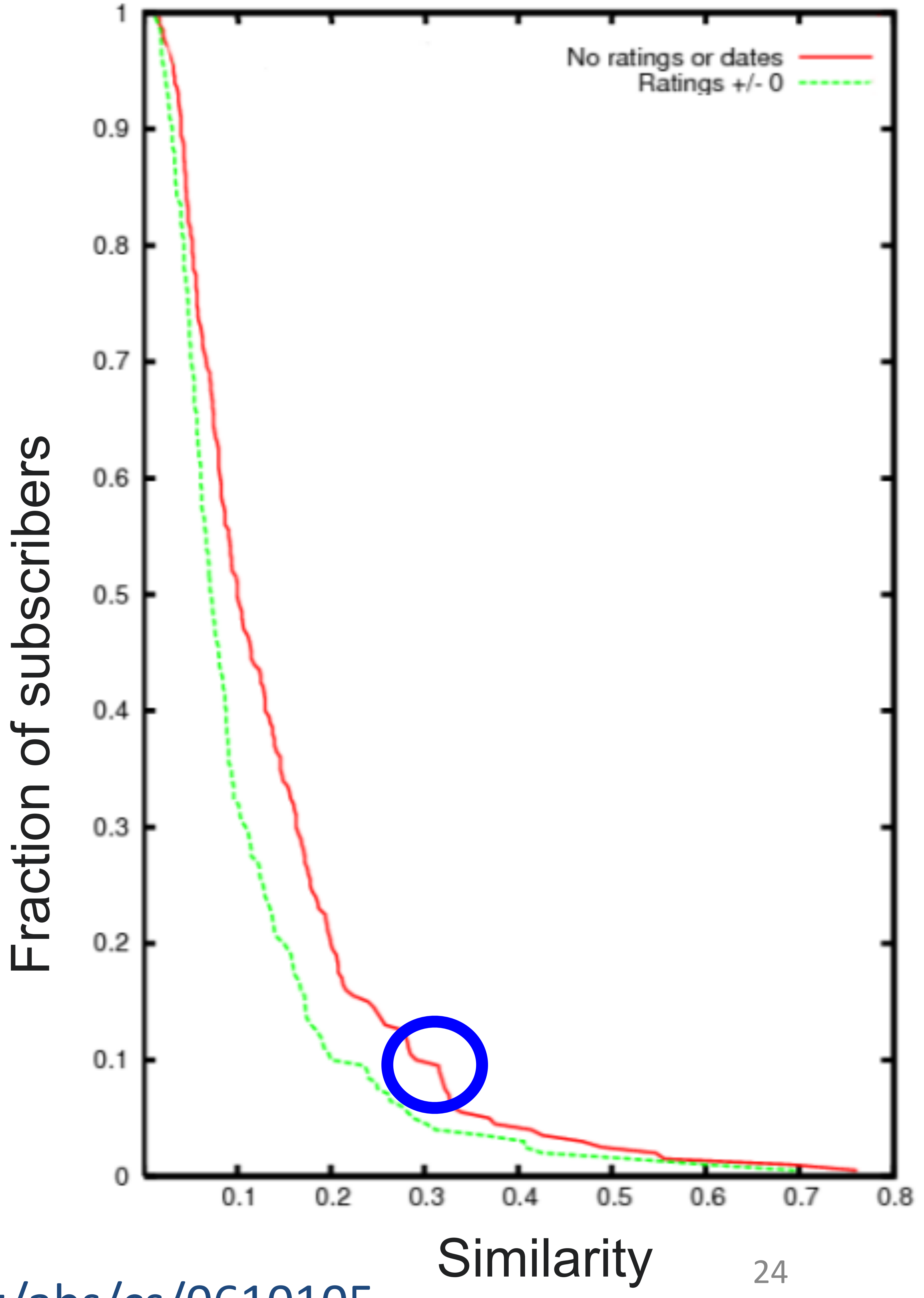

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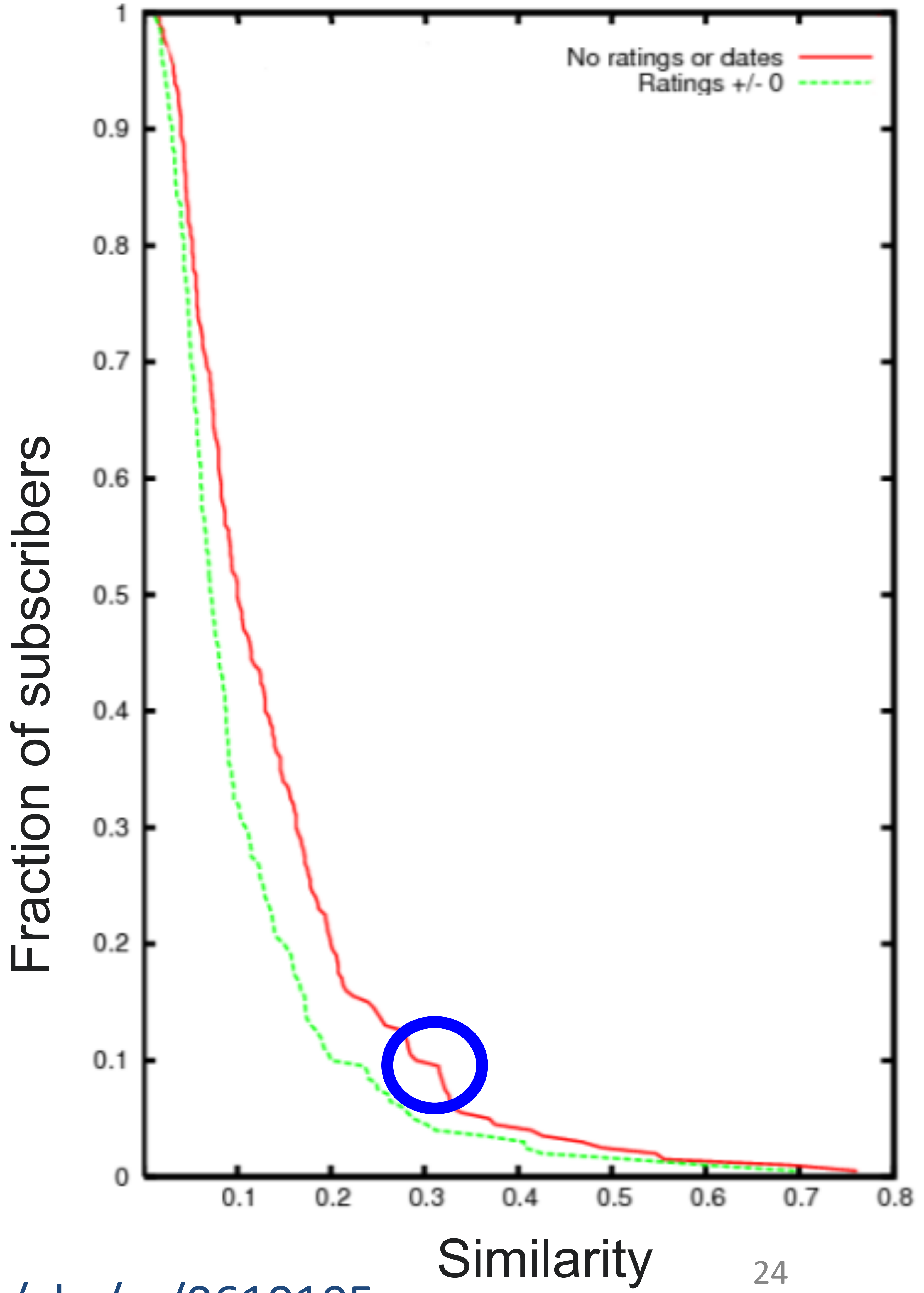

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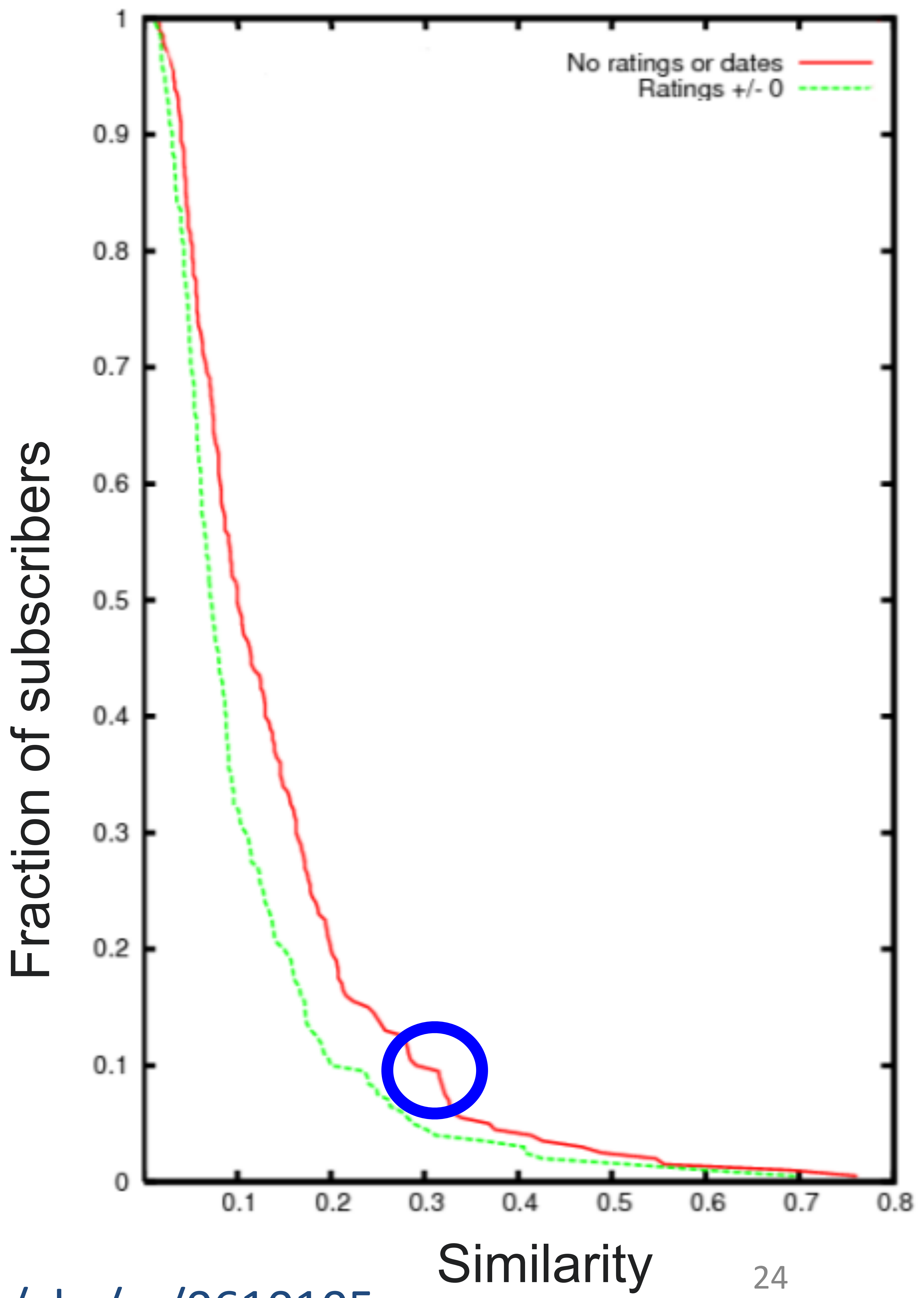

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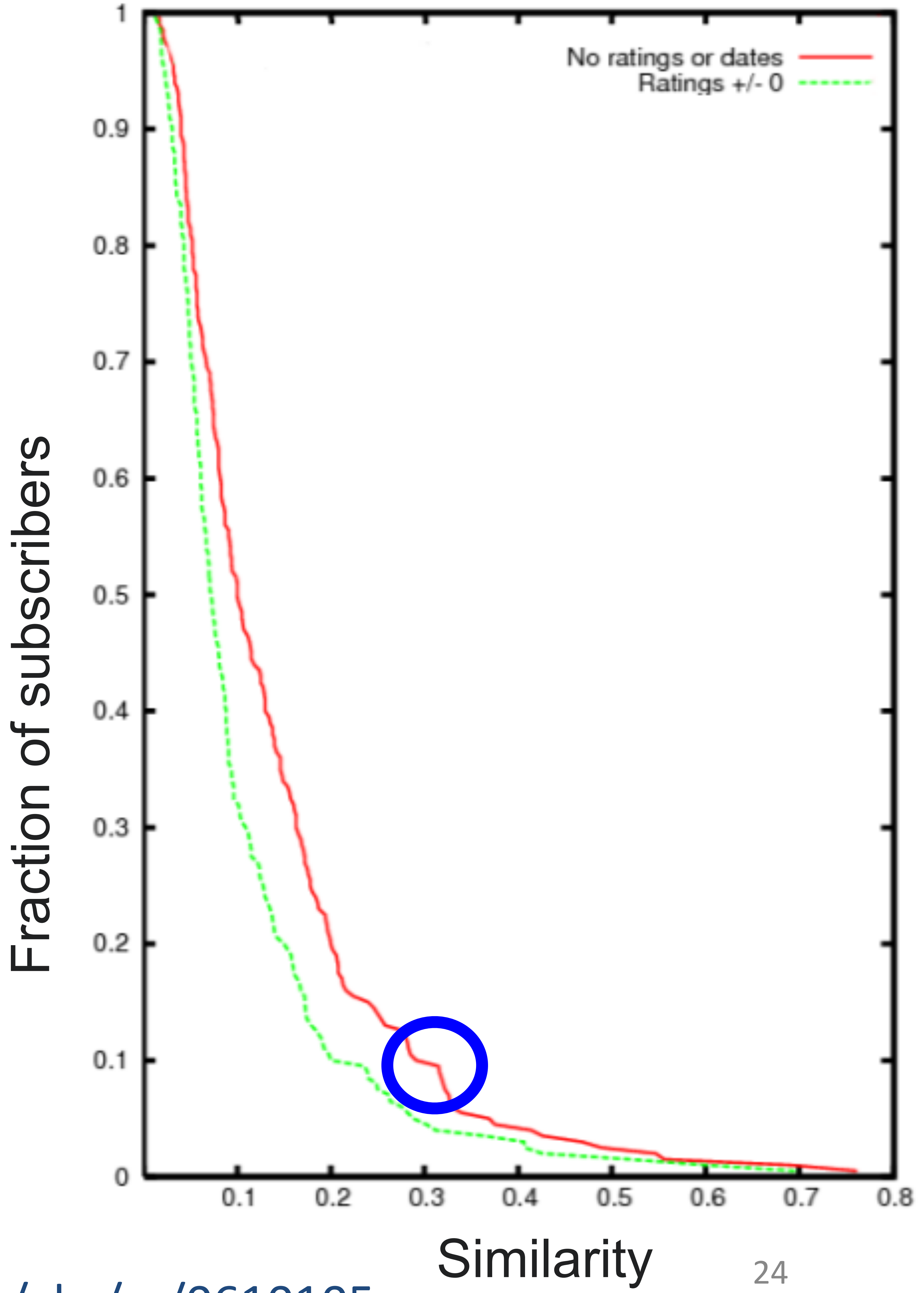
- Here, to make two records "close" the data is destroyed



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- Learn about movies that IMDb users didn’t want to tell the world: sexual orientation, religious beliefs, political attitude, etc.

Netflix Prize (2006)

Results of the attack

- With 8 movie ratings and dates that may have a 3-days error, 96% of Netflix clients whose data was released can be uniquely identified in the dataset
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Privacy is more than re-identification

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Medical encounter data

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- Ambulance collects an elderly neighbor

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- Re-identification fails to capture privacy risks!

NYC Taxi and Limo Commission (2014)

https://chriswhong.com/open-data/foil_nyc_taxi/

NYC Taxi and Limo Commission (2014)

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Taxi & Limousine Commission

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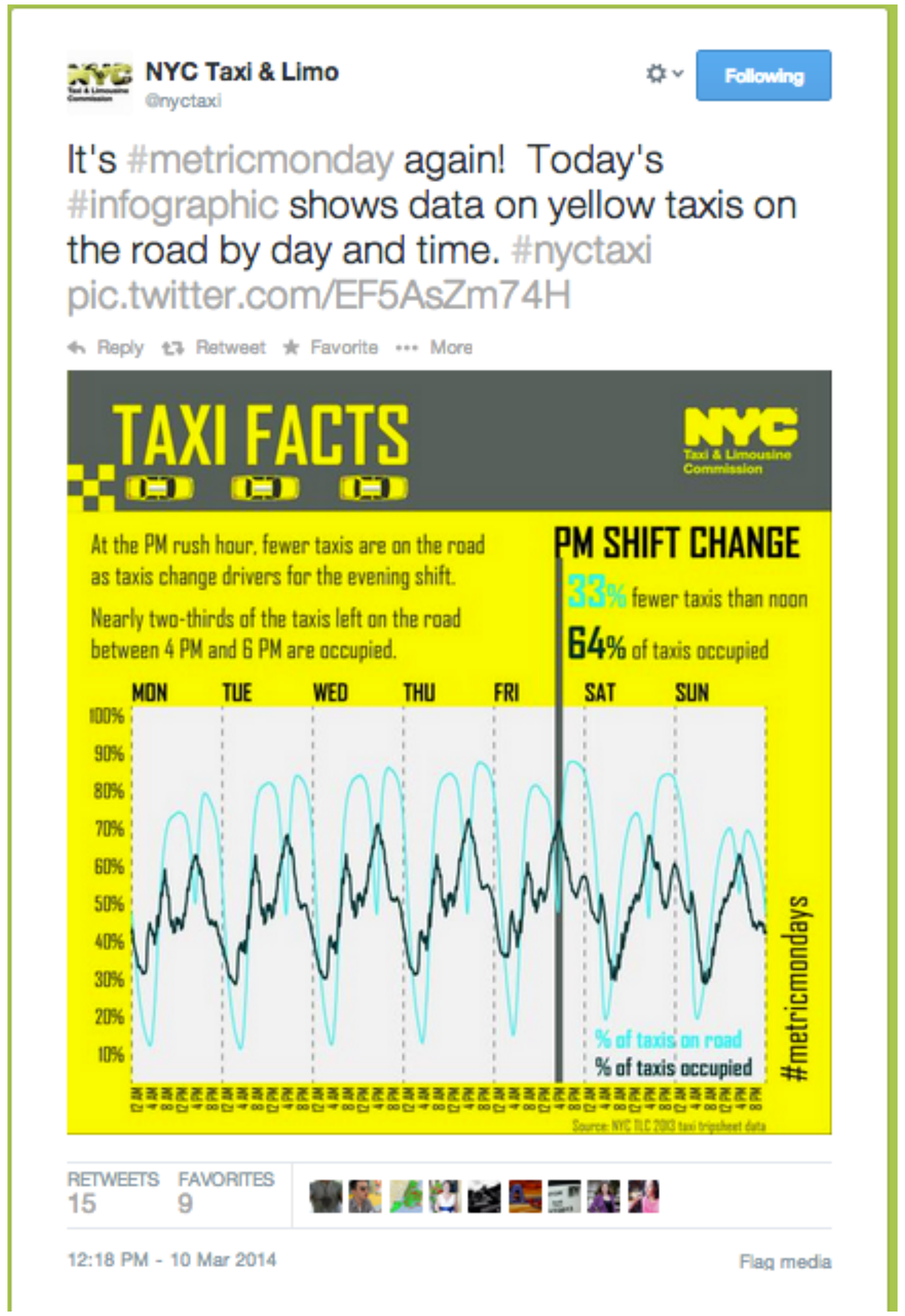
Taxi & Limousine Commission



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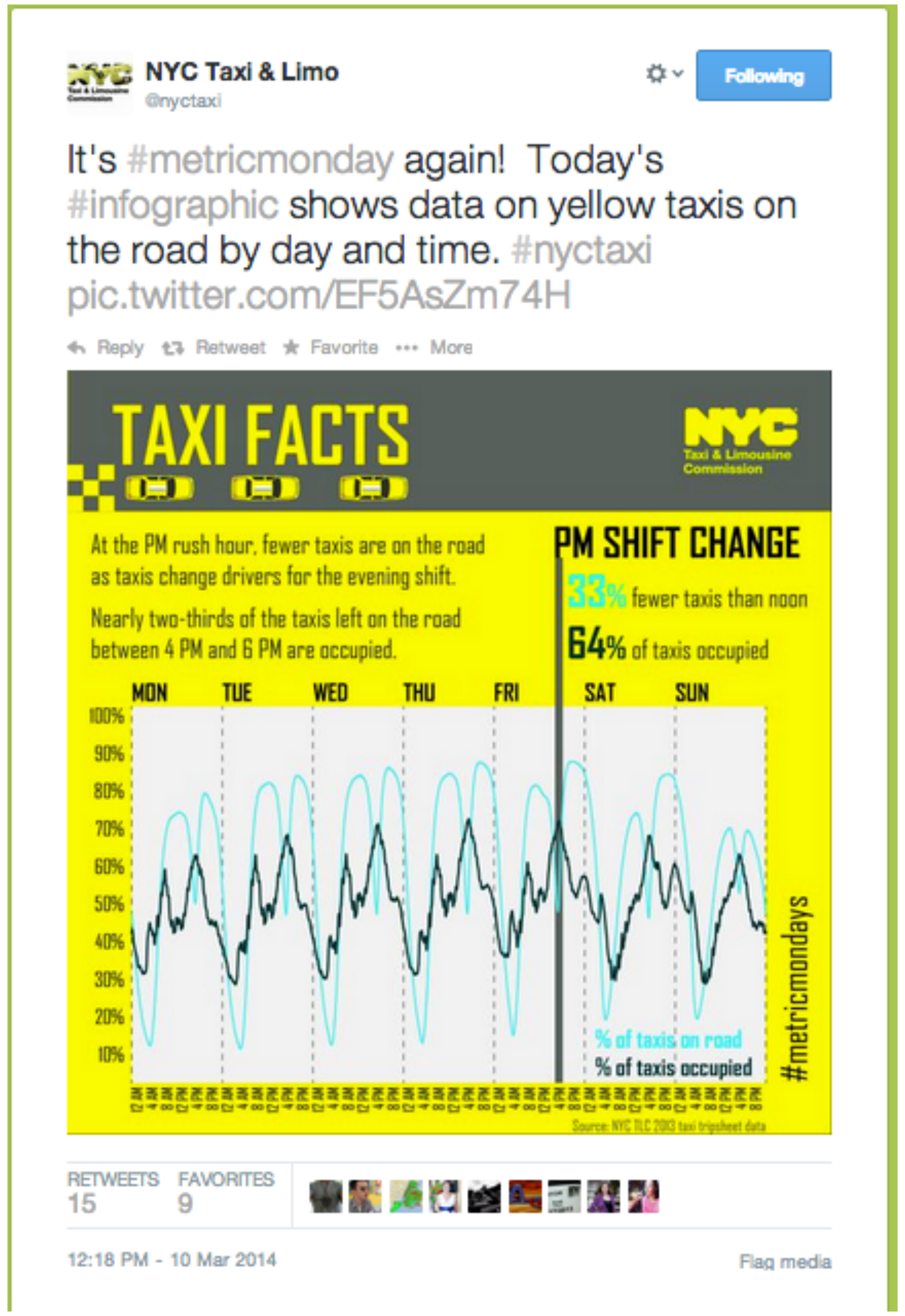

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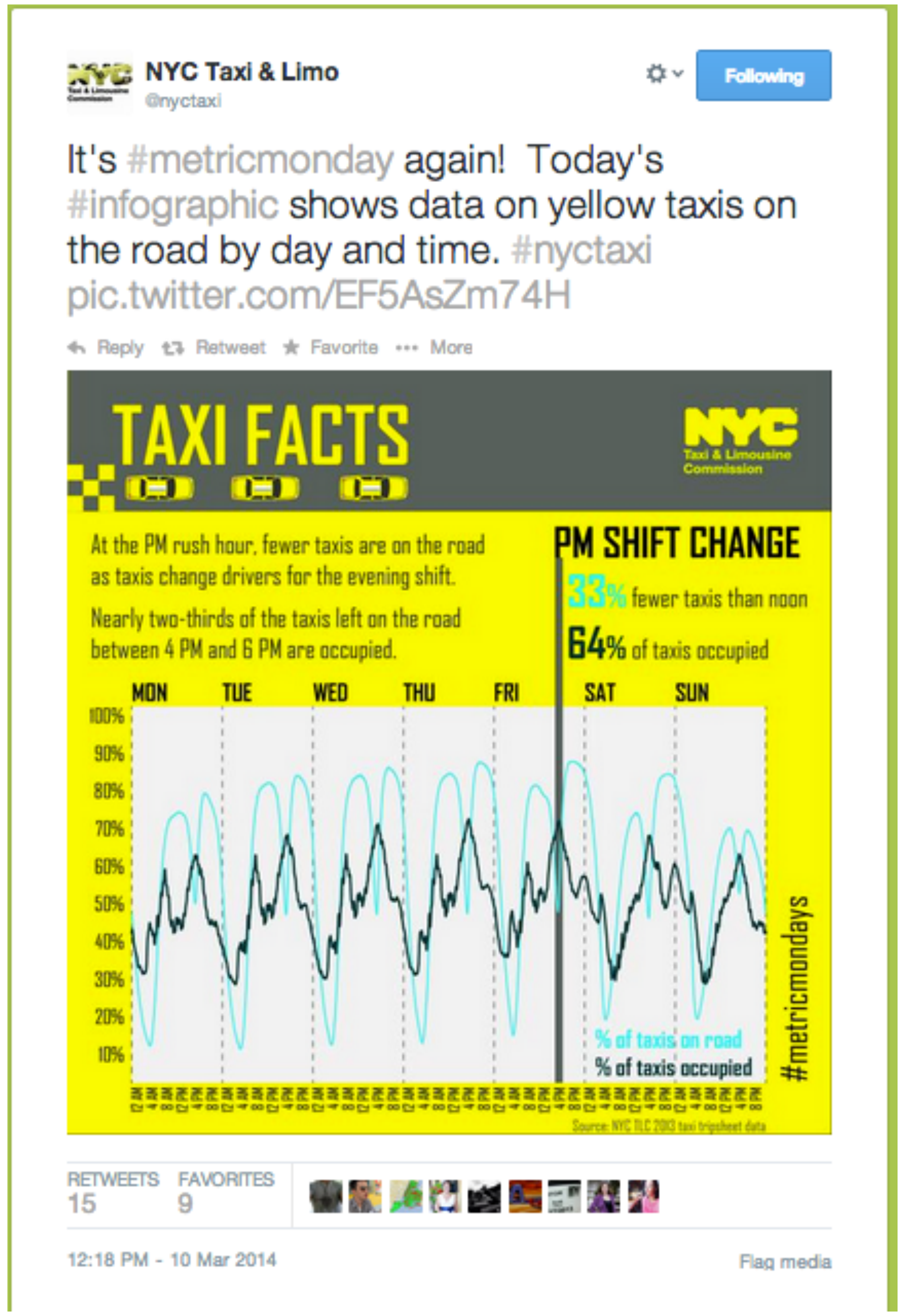

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NYC Taxi and Limo Commission (2014)

	A	B	C	D	E	F	G	H	I	J	K
1	medallion	hack_license	vendor_id	pickup_datetime	payment_type	fare_amoun	surcharge	mta_tax	tip_amount	tolls_amoun	total_amount
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3	0BD7C8F5BA12B88E0B67BED	9FD8F69F0804BDB5549F	CMT	1/6/13 0:18	CSH	6	0.5	0.5	0	0	7
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5	DFD2202EE08F7A8DC9A57B0	51EE87E3205C985EF843	CMT	1/7/13 23:54	CSH	5	0.5	0.5	0	0	6
6	DFD2202EE08F7A8DC9A57B0	51EE87E3205C985EF843	CMT	1/7/13 23:25	CSH	9.5	0.5	0.5	0	0	10.5
7	20D9ECB2CA0767CF7A01564	598CCE5B9C1918568DE	CMT	1/7/13 15:27	CSH	9.5	0	0.5	0	0	10
8	496644932DF3932605C22C7	513189AD756FF14FE670	CMT	1/8/13 11:01	CSH	6	0	0.5	0	0	6.5
9	0B57B9633A2FECD3D3B1944	CCD4367B417ED6634D9	CMT	1/7/13 12:39	CSH	34	0	0.5	0	4.8	39.3
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dropoff_datetime, passenger_count, trip_time_in_secs, trip_distance, pickup_longitude,
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- MD5 values of taxi number and driver license
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- MD5 values of taxi number and driver license
- After a taxi ride one can learn information about the driver
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```

- MD5 values of taxi number and driver license
- After a taxi ride one can learn information about the driver
- If someone is taking a taxi you can see where they’re going
- Are they good tippers

https://chriswhong.com/open-data/foil_nyc_taxi/

Class exercise

This work was performed using an anonymized mobile phone dataset that contains call information for ~1.5 M users of a mobile phone operator. The data collection took place from April 2006 to June 2007 in a western country. Each time a user interacts with the mobile phone operator network by initiating or receiving a call or a text message, the location of the connecting antenna is recorded [Fig. 1A]. The dataset's intrinsic spatial resolution is thus the maximal half-distance between antennas. The dataset's intrinsic temporal resolution is one hour [Fig. 1B].

...

On average, 114 interactions per user per month for the nearly 6500 antennas are recorded. Antennas in our database are distributed throughout the country and serve, on average, ~ 2000 inhabitants each, covering areas ranging from 0.15 km2 in cities to 15 km2 in rural areas.

...

The considered dataset contains one trace *T* for each user. The traces spatio-temporal points contain the region in which the user was and the time of the interaction.

Popular idea #2

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- Information not explicitly given cannot be harmful

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- E.g., redaction

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Probing [redacted] with *Kepler*
Mark Marley, auer, Jason Rowe
NASA Ames Research Center

Introduction

This white paper suggests a potentially high-reward secondary science target that may be appropriate to include during a revised Kepler planet search r is to be repurposed to observe a field on or near the ecliptic plane we suggest that [redacted] be included in the field of view. Assuming an appropriate fie dditional resources to observe this planet. A longterm [redacted] photometric series taken of [redacted] could potentially detect internal os net and open a new windo probing the interior structure of an ice giant. *Kepler* has demonstrated both that ice giants are common in the galaxy and the exceptional value of continuous photo nitoring for detecting and interpreting stellar oscillations. A *Kepler* observation of [redacted] would appropriately combine these two successes to perhaps similarly dissec ior structure of one of our own ice giants.

Scientific Background

The classes of solar system planets: the gas giants and the ice gian [redacted] with masses around 16 [redacted] asses comprise a distinct class from [redacted] es greater than about 1 [redacted] masses. The primary constituents [redacted] are likely ices surrounding ky core with a r hin atmospheric of h ich gas. *Kepler* has ably demonstrated that such [redacted] mass much more common than gas giants in fact—outside of th stem [redacted] It is thus important to understand the interior structure of these worlds in del their formation and evolution. Unfortunately our best data on the interior structure of these worlds comes from the gravitational harmonics measured during the single flybys of *Voyager* 2 about 25 years ago. Given the uncert armonics, a number of possible interior structu compositions are possible [redacted] Guillot [redacted] outlines a number of impo surrounding the ice giants, ng the s eir cores and the composition of their deep envelopes. Marley et al. [redacted] employed a Monte Carlo method for the construction of interior models and strated that the uncer ere sufficiently great that both [redacted] ell as continuously varying models were possible. Without new from the available data.

Seismology is "by far" [redacted] the most promising technique for constraining the core mass of the uncertainties that plague interior model inversion. In principle, for a fixed spherical harmonic degree, acoustic oscillation modes of sequentially higher order *n* penetrate progressively less deeply into the interior. Some oscillation modes thus "see" the core while others do not. The progression of mode frequencies—if observed—uniquely delineates the size of the planet's core as well as the structure of the envelope. The basic theo omputing giant planet oscillat be discussed a k a tsov et al. [redacted] and includes work by Mosser [redacted] for [redacted] and Marley [redacted] for [redacted]

The bee ber of searches for giant planet oscillations, primarily for [redacted]

Popular idea #2

Declassified and Approved
for Release, 10 April 2004

Bin Ladin Determined To Strike in US

Clandestine, foreign government, and media reports indicate Bin Ladin since 1997 has wanted to conduct terrorist attacks in the US. Bin Ladin implied in US television interviews in 1997 and 1998 that his followers would follow the example of World Trade Center bomber Ramzi Yousef and "bring the fighting to America."

After US missile strikes on his base in Afghanistan in 1998, Bin Ladin told followers he wanted to retaliate in Washington, according to a [redacted] service.

An Egyptian Islamic Jihad (EIJ) operative told an [redacted] service at the same time that Bin Ladin was planning to exploit the operative's access to the US to mount a terrorist strike.

The millennium plotting in Canada in 1999 may have been part of Bin Ladin's first serious attempt to implement a terrorist strike in the US. Convicted plotter Ahmed Ressam has told the FBI that he conceived the idea to attack Los Angeles International Airport himself, but that Bin Ladin lieutenant Abu Zubaydah encouraged him and helped facilitate the operation. Ressam also said that in 1998 Abu Zubaydah was planning his own US attack.

Ressam says Bin Ladin was aware of the Los Angeles operation.

Although Bin Ladin has not succeeded, his attacks against the US Embassies in Kenya and Tanzania in 1998 demonstrate that he prepares operations years in advance and is not deterred by setbacks. Bin Ladin associates surveilled our Embassies in Nairobi and Dar es Salaam as early as 1993, and some members of the Nairobi cell planning the bombings were arrested and deported in 1997.

Al-Qa'ida members—including some who are US citizens—have resided in or traveled to the US for years, and the group apparently maintains a support structure that could aid attacks. Two al-Qa'ida members found guilty in the conspiracy to bomb our Embassies in East Africa were US citizens, and a senior EIJ member lived in California in the mid-1990s.

A clandestine source said in 1998 that a Bin Ladin cell in New York was recruiting Muslim-American youth for attacks.

We have not been able to corroborate some of the more sensational threat reporting, such as that from a [redacted] service in 1998 saying that Bin Ladin wanted to hijack a US aircraft to gain the release of "Blind Shaykh" 'Umar 'Abd al-Rahman and other US-held extremists.

continued

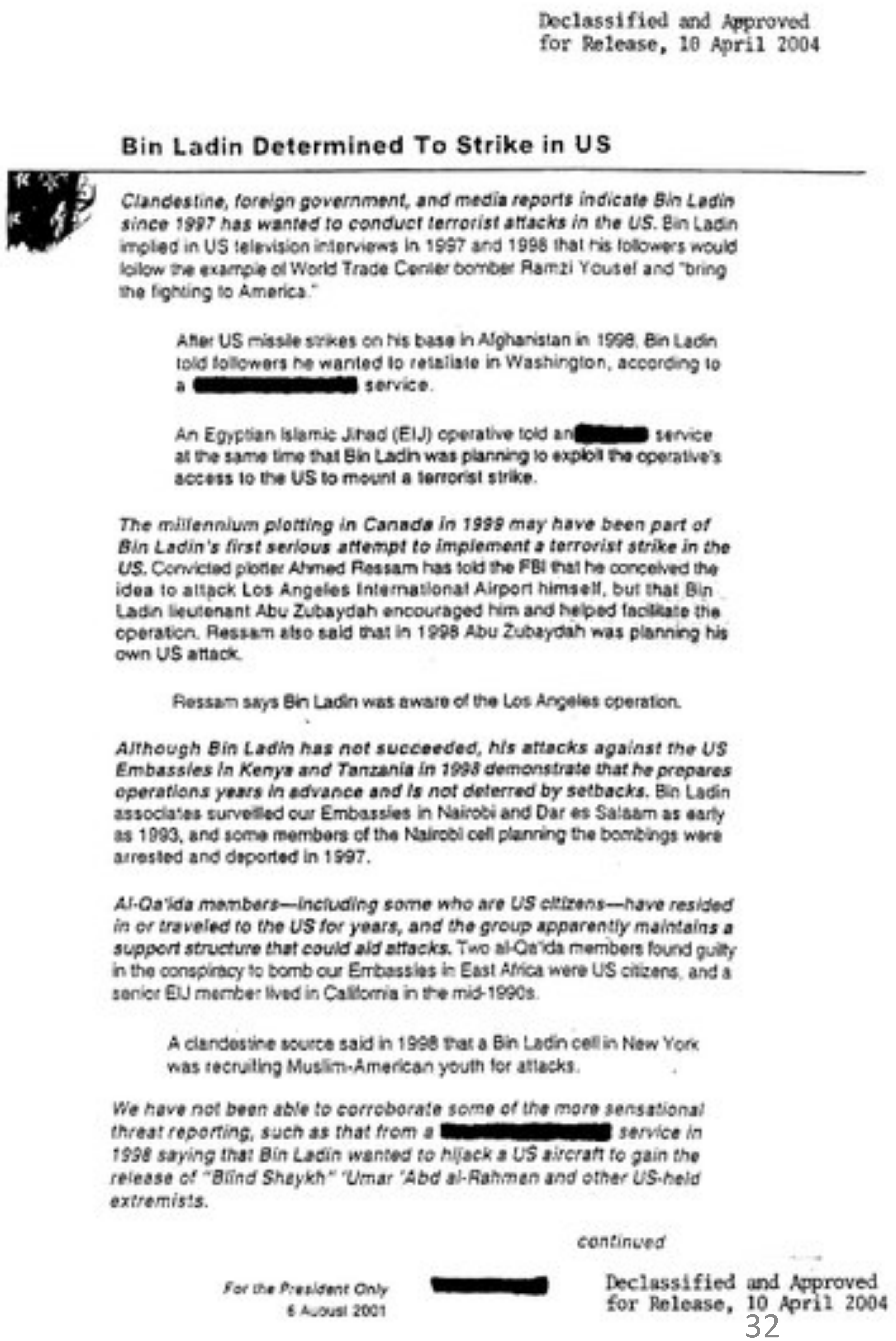
For the President Only
6 August 2001

[redacted]

Declassified and Approved
for Release, 10 April 2004

Popular idea #2

- The President's Daily Brief (PDB) is a top-secret document given each morning to the US president



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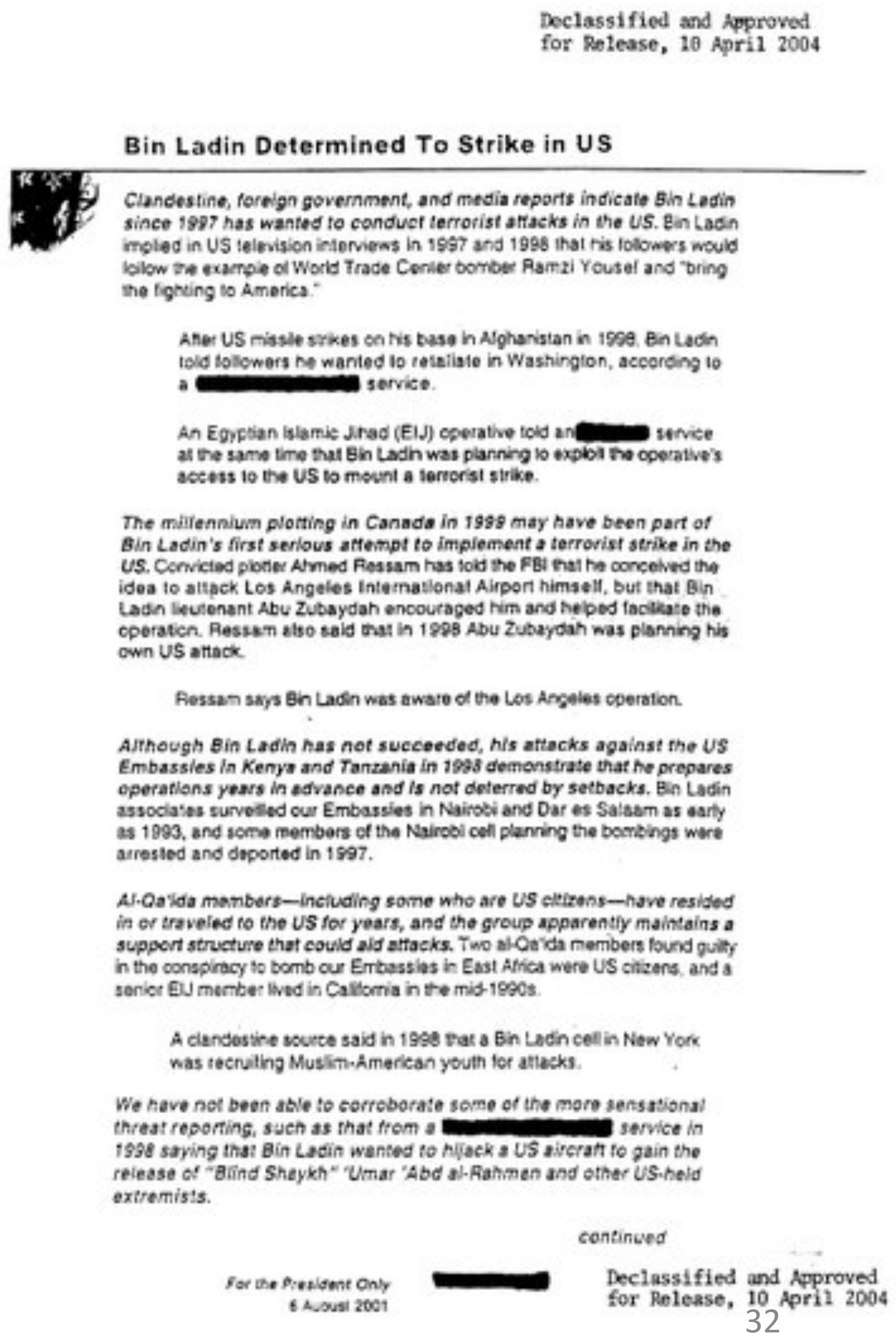

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continued

For the President Only
6 August 2001 [redacted]

Declassified and Approved for Release, 10 April 2004

Popular idea #2

An Egyptian Islamic Jihad (EIJ) operative told an [redacted] service at the same time that Bin Ladin was planning to exploit the operative's access to the US to mount a terrorist strike.

Popular idea #2

- Naccache and Whelan analyzed the geometry of the font

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- The "an" reduced to 7 candidates: Ukrainian, uninvited, unofficial, incursive, Egyptian, indebted and Ugandan

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- Naccache and Whelan analyzed the geometry of the font
- 1530 plausible words
- The "an" reduced to 7 candidates: Ukrainian, uninvited, unofficial, incursive, Egyptian, indebted and Ugandan
- Egyptian is the only one who made sense in the context

An Egyptian Islamic Jihad (EIJ) operative told an [redacted] service at the same time that Bin Ladin was planning to exploit the operative's access to the US to mount a terrorist strike.

Class exercise

If I sorted our class list by NUID, the 37th, or median person in our class is [redacted], who is originally from [redacted] but currently lives in [redacted].

Identifiers vs. Sensitive attributes

Identifiers vs. Sensitive attributes

- Key attributes: name, address, etc. (uniquely identifying)

Identifiers vs. Sensitive attributes

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- Quasi-identifiers: ZIP, DoB, etc.

Identifiers vs. Sensitive attributes

- Key attributes: name, address, etc. (uniquely identifying)
- Quasi-identifiers: ZIP, DoB, etc.
- Sensitive attributes: medical records, etc.

Identifiers vs. Sensitive attributes

- Key attributes: name, address, etc. (uniquely identifying)
- Quasi-identifiers: ZIP, DoB, etc.
- Sensitive attributes: medical records, etc.

Key Attribute		Quasi-identifier		Sensitive attribute
Name	DOB	Gender	Zipcode	Disease
Andre	1/21/76	Male	53715	Heart Disease
Beth	4/13/86	Female	53715	Hepatitis
Carol	2/28/76	Male	53703	Brochitis
Dan	1/21/76	Male	53703	Broken Arm
Ellen	4/13/86	Female	53706	Flu
Eric	2/28/76	Female	53706	Hang Nail

k-Anonymity (Sweeney and Samarati 98)

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- Any quasi-identifier present in the released table must appear in at least k records
- Simple and syntactic property of the dataset
- Very popular technique

k-Anonymity (Sweeney and Samarati 98)

	Race	Birth	Gender	ZIP	Problem
t1	Black	1965	m	0214*	short breath
t2	Black	1965	m	0214*	chest pain
t3	Black	1965	f	0213*	hypertension
t4	Black	1965	f	0213*	hypertension
t5	Black	1964	f	0213*	obesity
t6	Black	1964	f	0213*	chest pain
t7	White	1964	m	0213*	chest pain
t8	White	1964	m	0213*	obesity
t9	White	1964	m	0213*	short breath
t10	White	1967	m	0213*	chest pain
t11	White	1967	m	0213*	chest pain

Figure 2 Example of *k*-anonymity, where *k*=2 and QI={*Race*, *Birth*, *Gender*, *ZIP*}

https://epic.org/privacy/reidentification/Sweeney_Article.pdf

k-Anonymity (Sweeney and Samarati 98)

Released table

	Race	Birth	Gender	ZIP	Problem
t1	Black	1965	m	0214*	short breath
t2	Black	1965	m	0214*	chest pain
t3	Black	1965	f	0213*	hypertension
t4	Black	1965	f	0213*	hypertension
t5	Black	1964	f	0213*	obesity
t6	Black	1964	f	0213*	chest pain
t7	White	1964	m	0213*	chest pain
t8	White	1964	m	0213*	obesity
t9	White	1964	m	0213*	short breath
t10	White	1967	m	0213*	chest pain
t11	White	1967	m	0213*	chest pain

External data source

Name	Birth	Gender	ZIP	Race
Andre	1964	m	02135	White
Beth	1964	f	55410	Black
Carol	1964	f	90210	White
Dan	1967	m	02174	White
Ellen	1968	f	02237	White

https://epic.org/privacy/reidentification/Sweeney_Article.pdf

k-Anonymity (Sweeney and Samarati 98)

Microdata

QID			SA
Zipcode	Age	Sex	Disease
47677	29	F	Ovarian Cancer
47602	22	F	Ovarian Cancer
47678	27	M	Prostate Cancer
47905	43	M	Flu
47909	52	F	Heart Disease
47906	47	M	Heart Disease

Generalized table

QID			SA
Zipcode	Age	Sex	Disease
476**	2*	*	Ovarian Cancer
476**	2*	*	Ovarian Cancer
476**	2*	*	Prostate Cancer
4790*	[43,52]	*	Flu
4790*	[43,52]	*	Heart Disease
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- Released table is 3-anonymous

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- Alice’s quasi-identifier (47677, 29, F) does not reveal her disease

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k-Anonymity (Sweeney and Samarati 98)

- Unsorted matching attack

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k-Anonymity (Sweeney and Samarati 98)

- Unsorted matching attack

Race	ZIP
Asian	02138
Asian	02139
Asian	02141
Asian	02142
Black	02138
Black	02139
Black	02141
Black	02142
White	02138
White	02139
White	02141
White	02142

PT

Race	ZIP
Person	02138
Person	02139
Person	02141
Person	02142
Person	02138
Person	02139
Person	02141
Person	02142
Person	02138
Person	02139
Person	02141
Person	02142

GT1

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k-Anonymity (Sweeney and Samarati 98)

- Unsorted matching attack
- Records appear in the same order as in the original table

Race	ZIP
Asian	02138
Asian	02139
Asian	02141
Asian	02142
Black	02138
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Black	02142
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White	02139
White	02141
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PT

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GT1

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k-Anonymity (Sweeney and Samarati 98)

- Unsorted matching attack
- Records appear in the same order as in the original table
- Solution: randomize order before releasing

Race	ZIP
Asian	02138
Asian	02139
Asian	02141
Asian	02142
Black	02138
Black	02139
Black	02141
Black	02142
White	02138
White	02139
White	02141
White	02142

PT

Race	ZIP
Person	02138
Person	02139
Person	02141
Person	02142
Person	02138
Person	02139
Person	02141
Person	02142
Person	02138
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Person	02141
Person	02142

GT1

https://epic.org/privacy/reidentification/Sweeney_Article.pdf

K-anonymity republishing attack

Race	BirthDate	Gender	ZIP	Problem
black	1965	male	02141	short of breath
black	1965	male	02141	chest pain
person	1965	female	0213*	painful eye
person	1965	female	0213*	wheezing
black	1964	female	02138	obesity
black	1964	female	02138	chest pain
white	1964	male	0213*	short of breath
person	1965	female	0213*	hypertension
white	1964	male	0213*	obesity
white	1964	male	0213*	fever
white	1967	male	02138	vomiting
white	1967	male	02138	back pain

GT1

Race	BirthDate	Gender	ZIP	Problem
black	1965	male	02141	short of breath
black	1965	male	02141	chest pain
black	1965	female	02138	painful eye
black	1965	female	02138	wheezing
black	1964	female	02138	obesity
black	1964	female	02138	chest pain
white	1960-69	male	02138	short of breath
white	1960-69	human	02139	hypertension
white	1960-69	human	02139	obesity
white	1960-69	human	02139	fever
white	1960-69	male	02138	vomiting
white	1960-69	male	02138	back pain

GT3

Quiz: what does k-Anonymity provide

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  attacker cannot tell that a given person has a certain sensitive attribute
- Identity discloser:
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This interpretation is correct,
assuming the attacker does not know anything other than quasi-identifiers

A chain of measures and counter measures

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- k-anonymity [Sweeney and Samarati 98]

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  Proposed L-diversity
- Attacks against L-diversity [Xiao and Tao 07]
  Proposed M-invariance
- Proposed T-closeness [Li et al. 07]

- Attacks against all the above [Ganta, Kasiviswanathan, Smith 08]

Query auditing

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- Refuse to answer queries that would compromise privacy

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Queries

$q_1 \ldots,\ q_{n-1}$

dataset

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Query auditing

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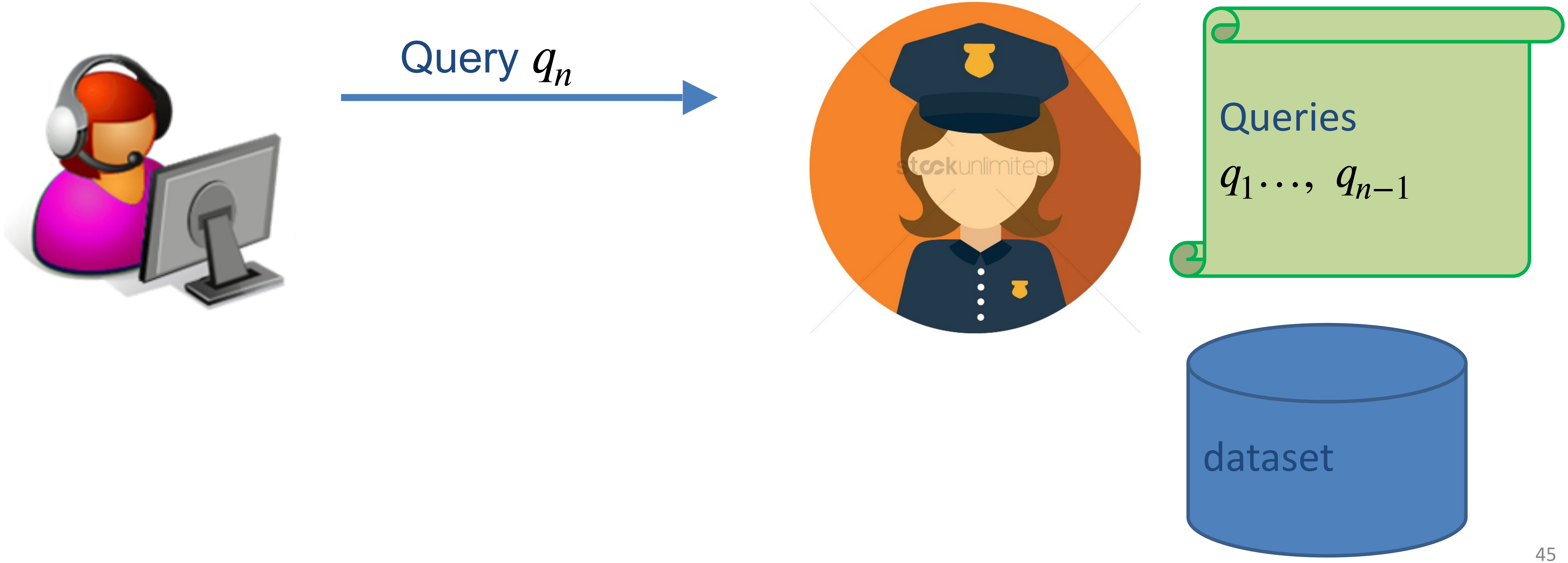

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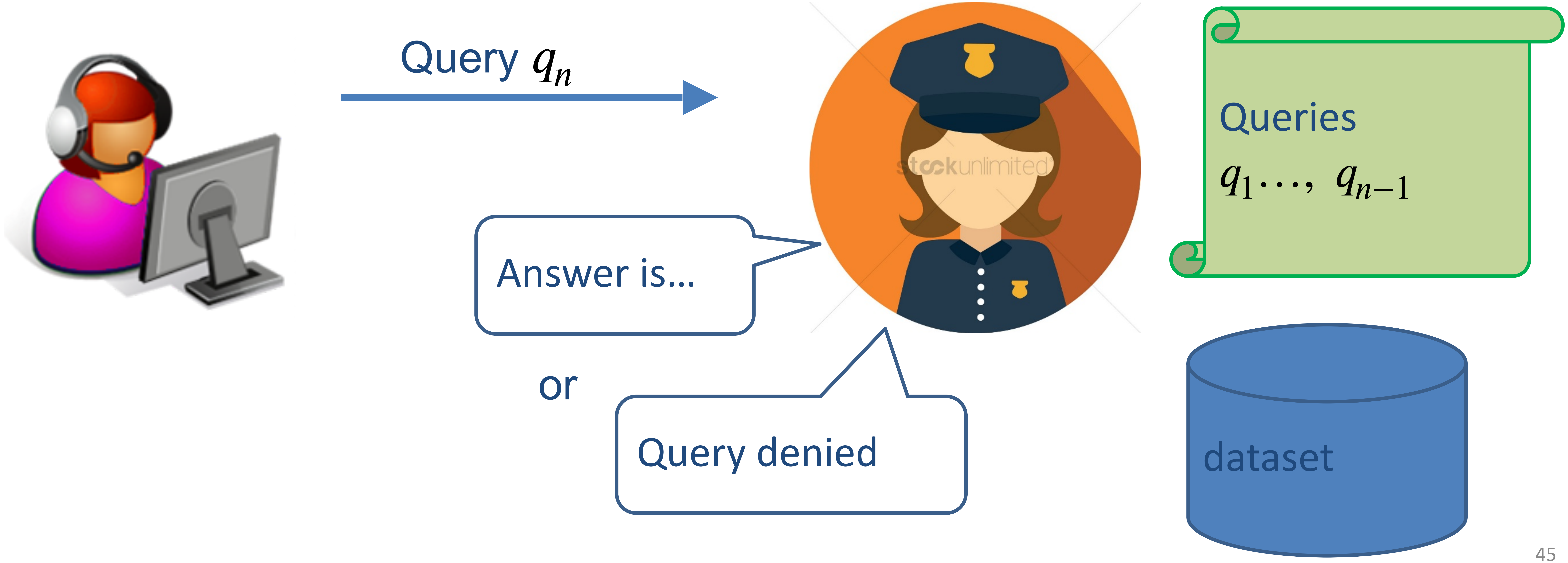
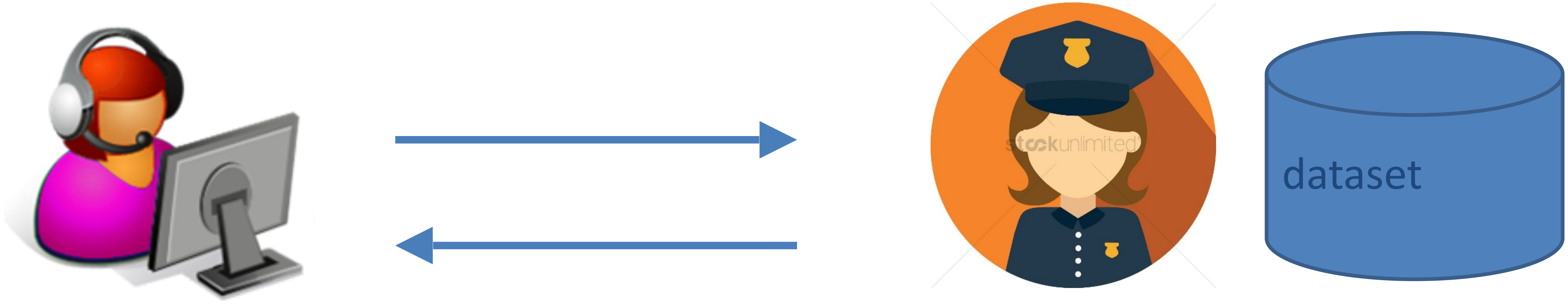


Example: sum/max auditing

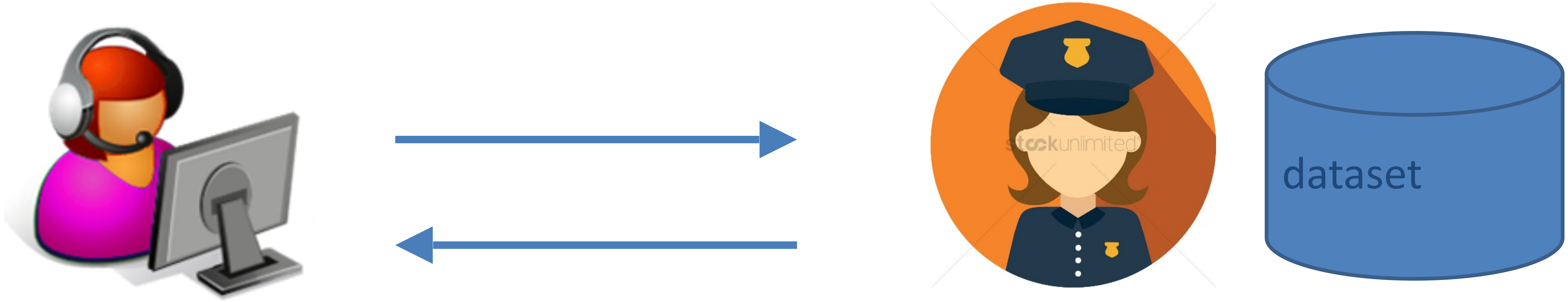
- Sensitive info: d_i (real)



Example: sum/max auditing

- Sensitive info: d_i (real)

$$q_1 = \mathrm{sum}\left(\mathrm{d}_1, \mathrm{d}_2, \mathrm{d}_3\right)$$



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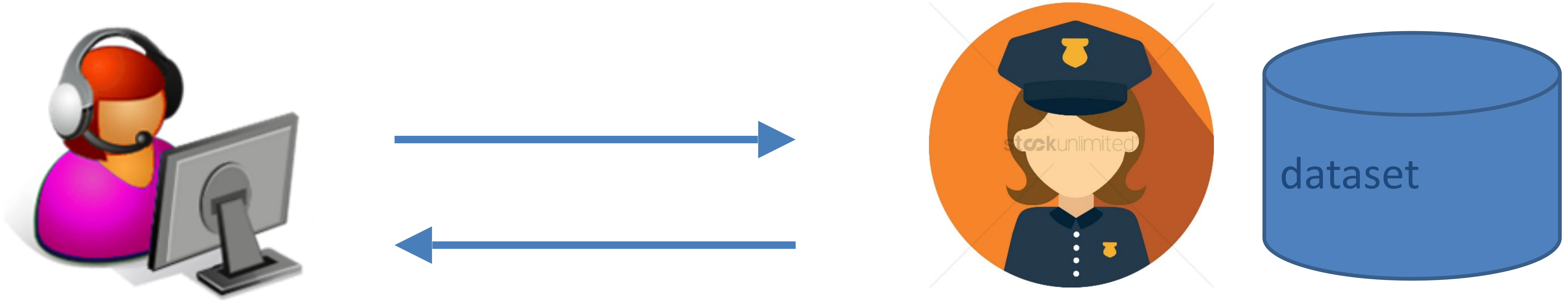
$$q_1 = \text{sum}\left(\text{d}_1, \text{d}_2, \text{d}_3\right)$$

$$\text{sum}\left(\text{d}_1, \text{d}_2, \text{d}_3\right) = 15$$



Example: sum/max auditing

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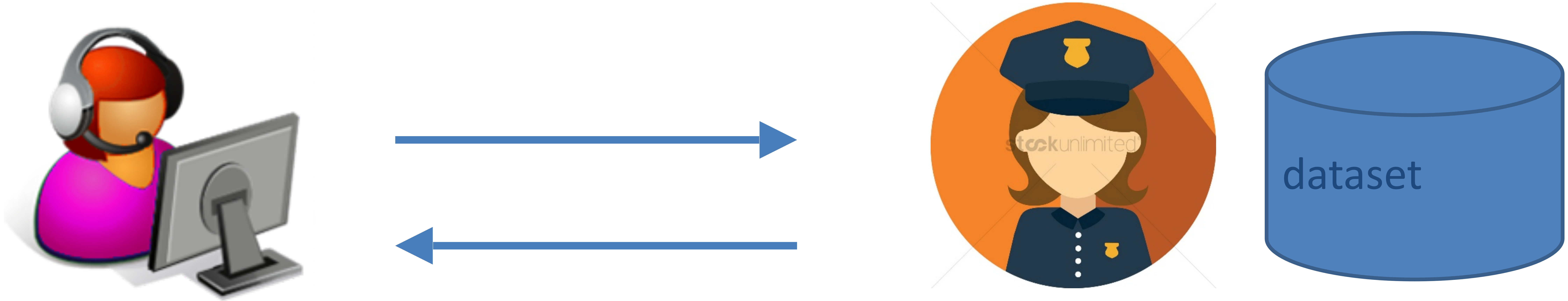
$q_1 = \text{sum}(\text{d}_1, \text{d}_2, \text{d}_3)$

$\text{sum}(\text{d}_1, \text{d}_2, \text{d}_3) = 15$

$q_2 = \max(\text{d}_1, \text{d}_2, \text{d}_3)$



Example: sum/max auditing

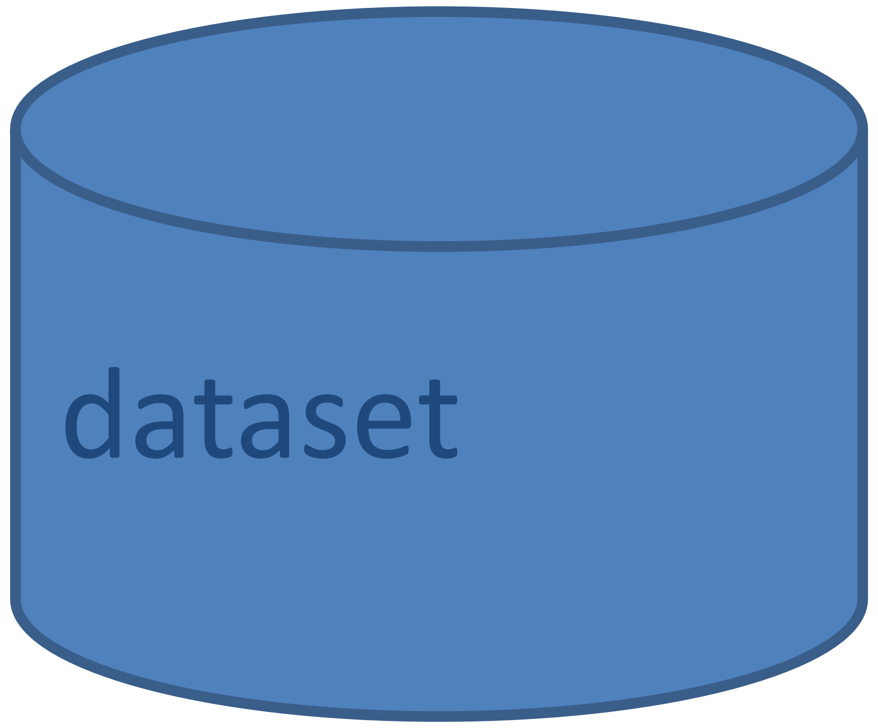
- Sensitive info: d_i (real)

$q_1 = \text{sum}\left(\mathrm{d}_1, \mathrm{d}_2, \mathrm{d}_3\right)$

$q_2 = \max\left(\mathrm{d}_1, \mathrm{d}_2, \mathrm{d}_3\right)$

$\text{sum}\left(\mathrm{d}_1, \mathrm{d}_2, \mathrm{d}_3\right) = 15$

query denied



Example: sum/max auditing

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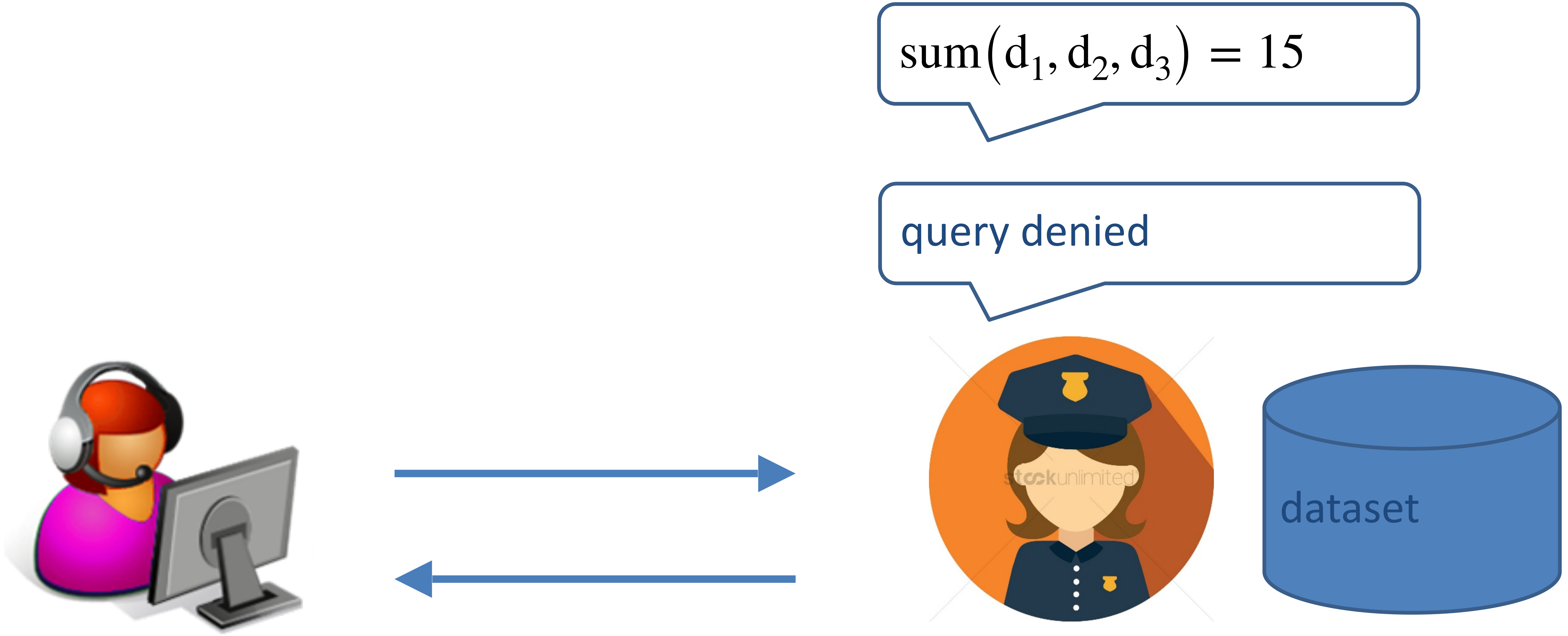


Example: sum/max auditing

- Sensitive info: d_i (real)

$\max(d_1, d_2, d_3) \geq 5$

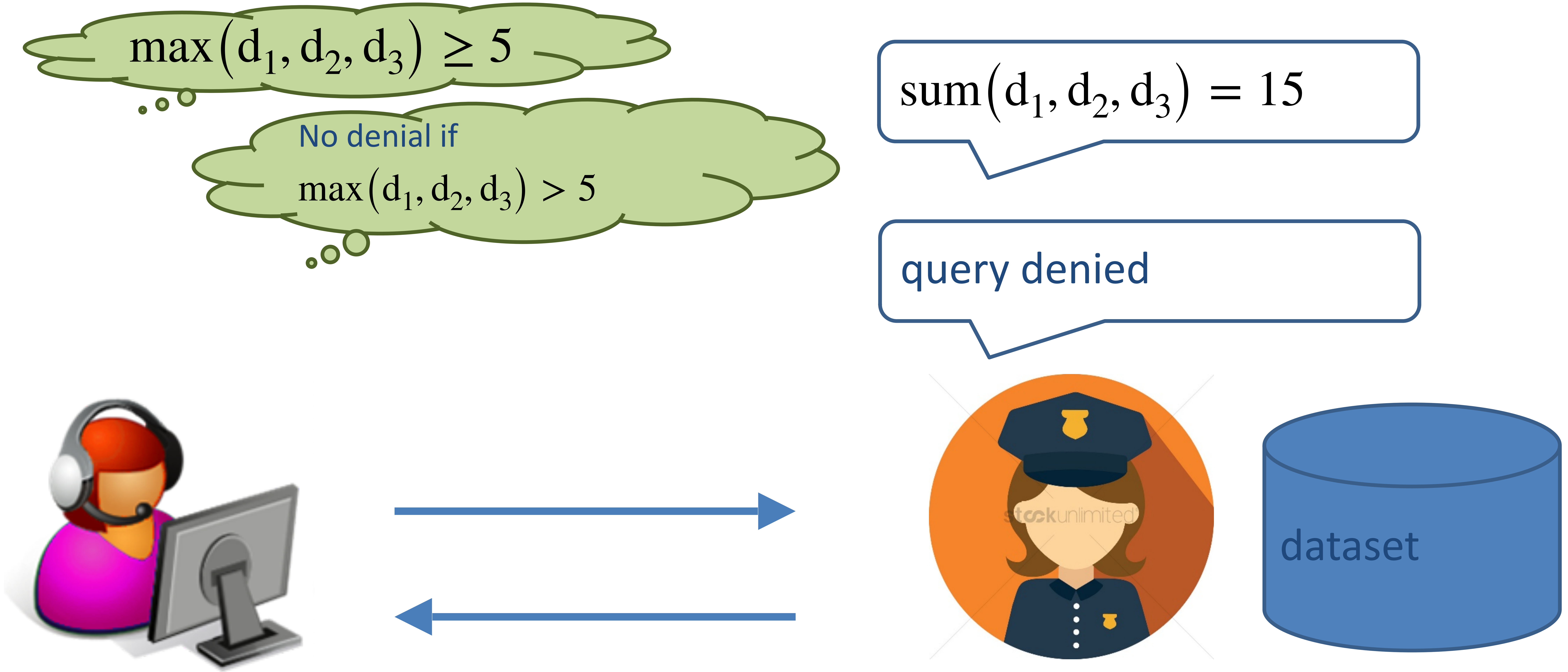
$\text{sum}(d_1, d_2, d_3) = 15$

query denied

dataset

Example: sum/max auditing

- Sensitive info: d_i (real)



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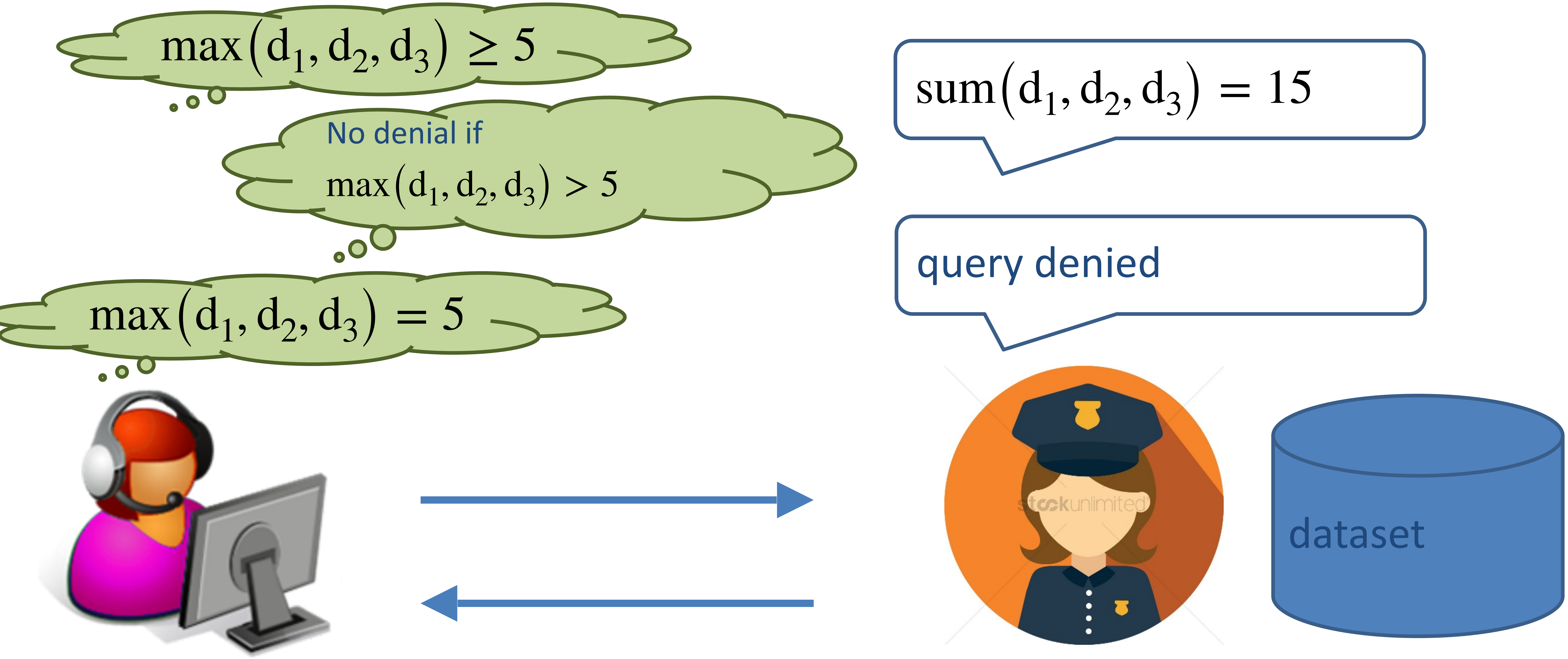

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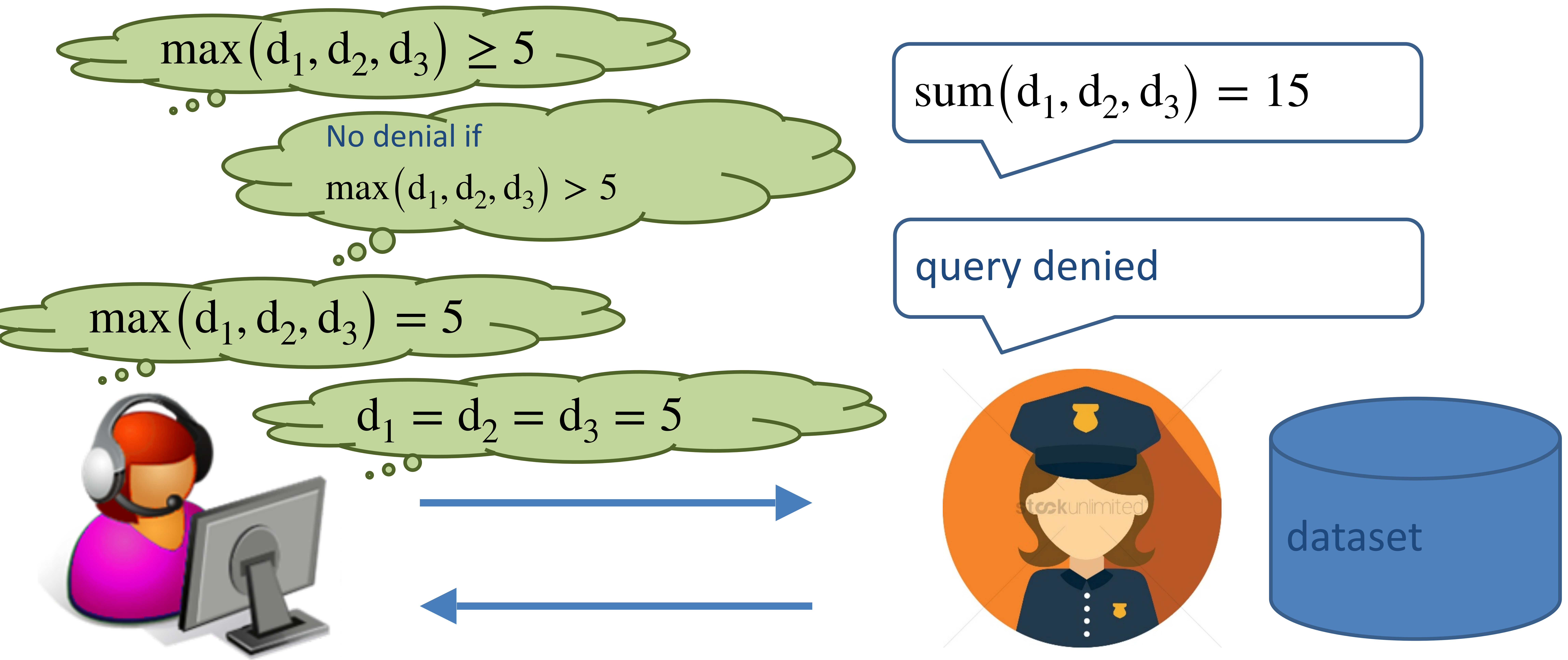

Popular idea #3: just add noise

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- Mask numbers by adding a random number between $[-a, a]$
  - Privacy $2a$ @ 100% confidence, Privacy a @ 50% confidence, …

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- The larger the interval the better the privacy

Popular idea #3: just add noise

- Mask numbers by adding a random number between $[-a, a]$
  - Privacy $2a @ 100\%$ confidence, Privacy $a @ 50\%$ confidence, …
- The larger the interval the better the privacy
- Example:
  - For each person mask age by adding a random number between $[-100, 100]$
  - Gives privacy 200@100% confidence
  - But, masked age -99 $\Rightarrow$ a baby of age 0 or 1

So far

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- Many ideas fall short of providing data privacy

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- Auxiliary information

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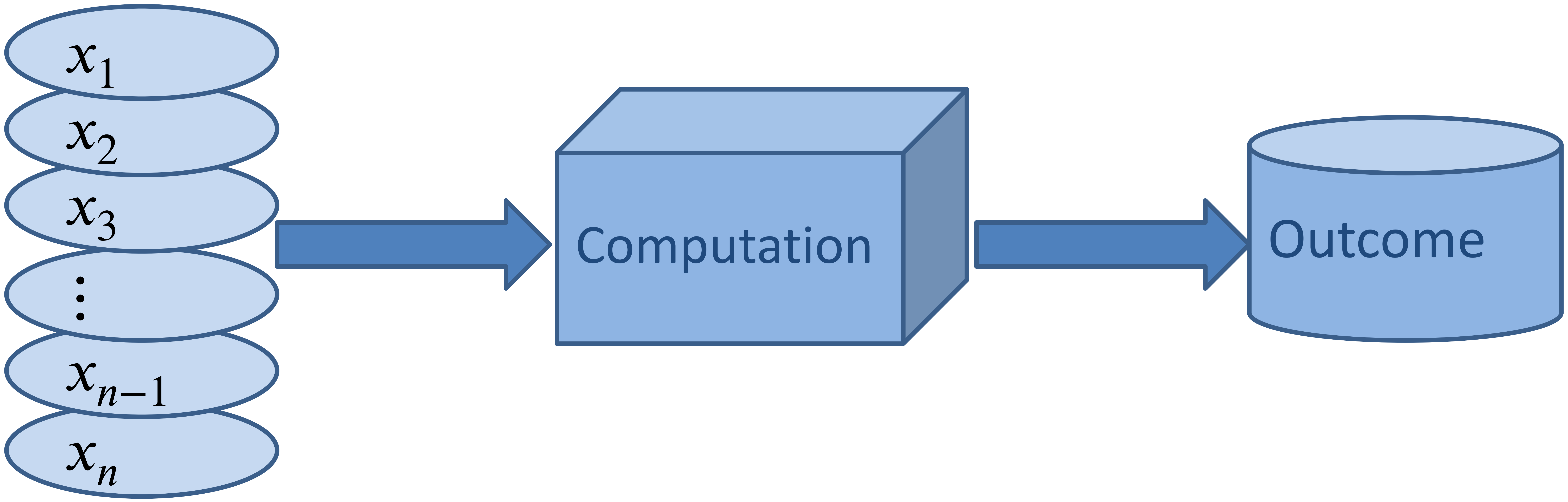
- Many ideas fall short of providing data privacy
- Auxiliary information
- Data itself may leak information
- Sparse dataset cannot be anonymized
- Privacy is more than re-identifying

Outline

- Popular ideas that do not work
  + privacy horror stories

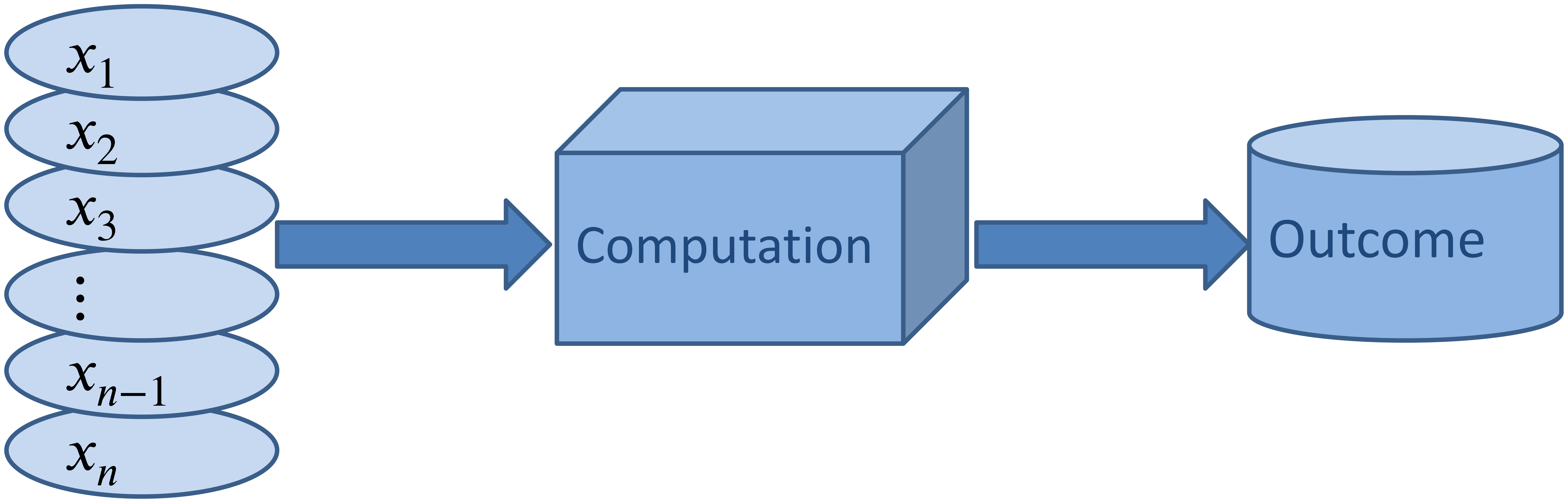
- An approach that works

What went wrong?



What went wrong?

Privacy is NOT a property of the outcome but of the computation!!!



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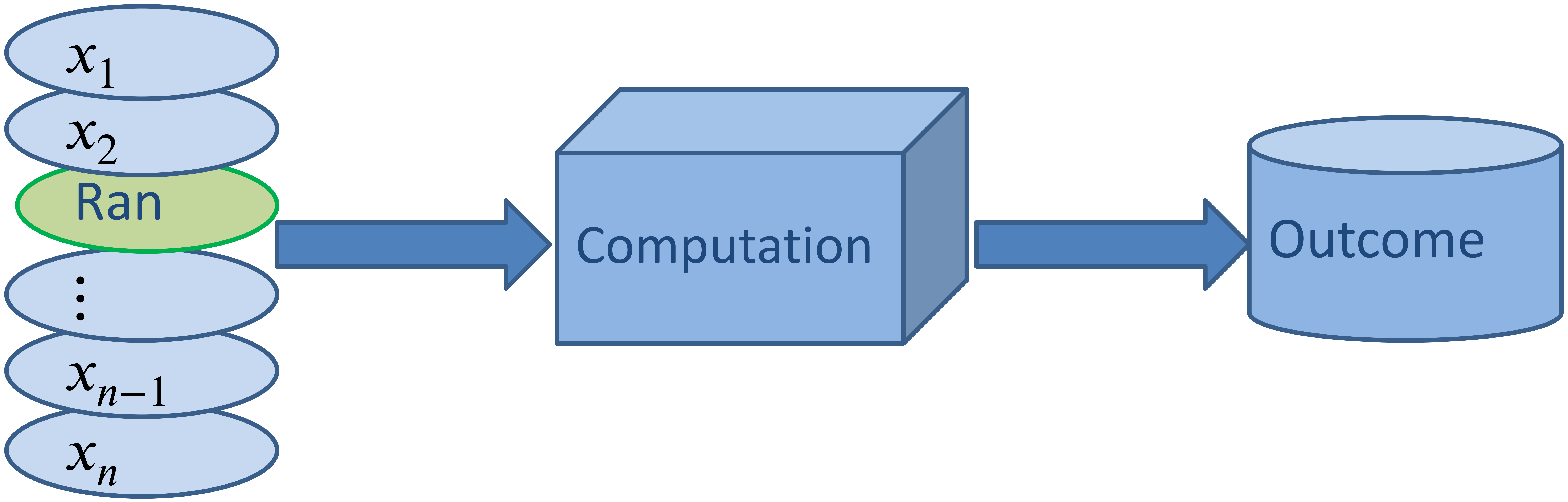

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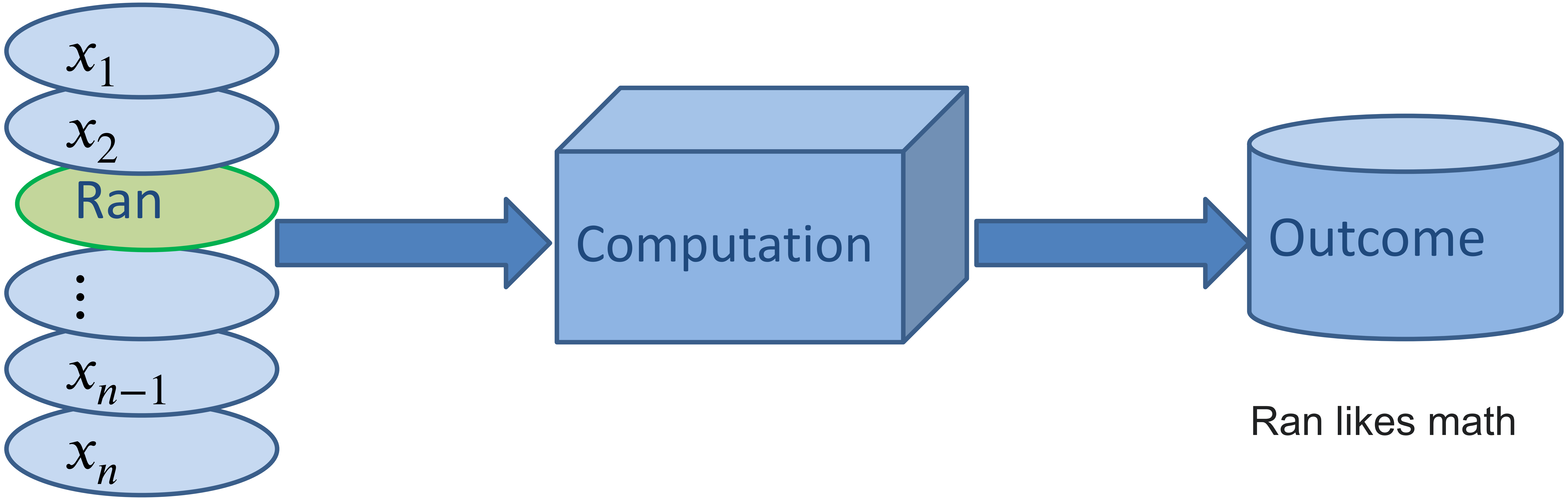

Ran likes math

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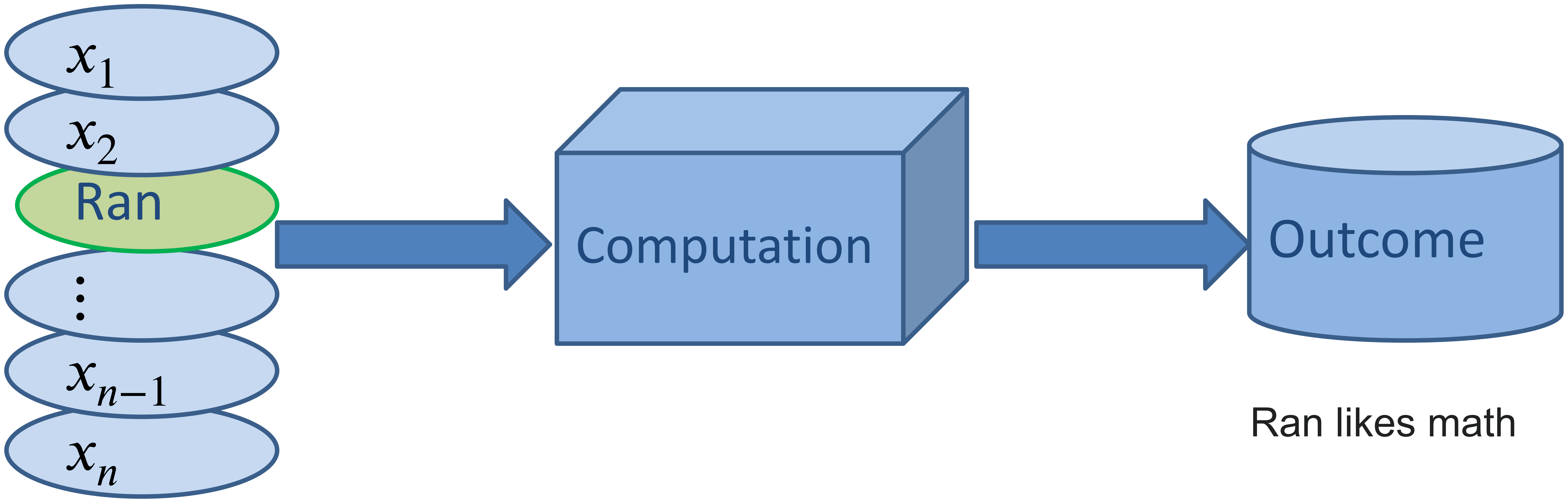

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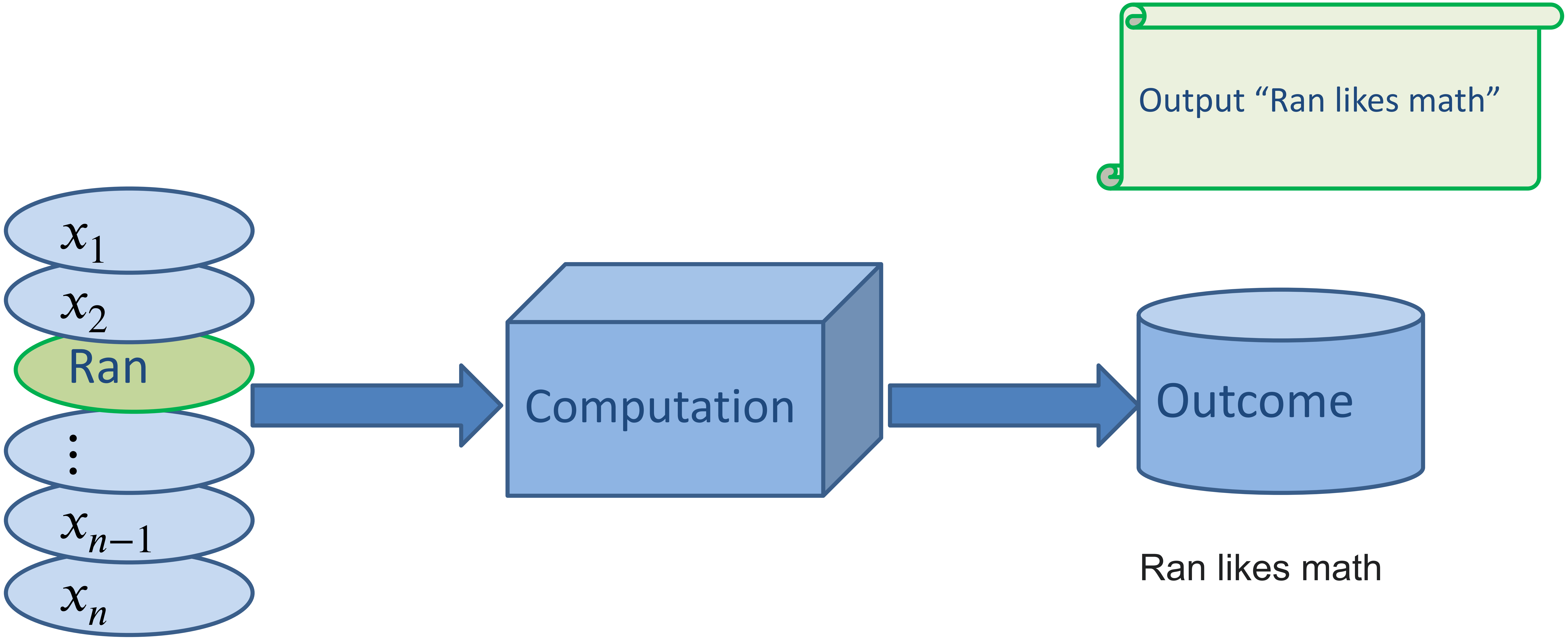
Is my privacy breached? Yes / No / Cannot tell

What went wrong?



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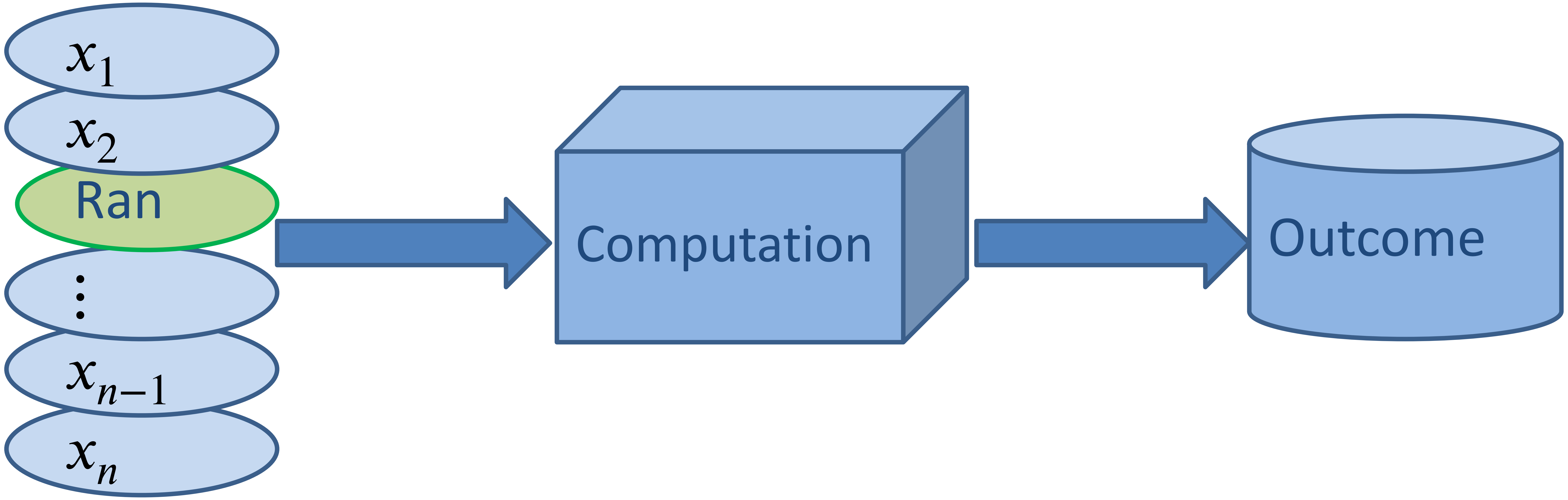

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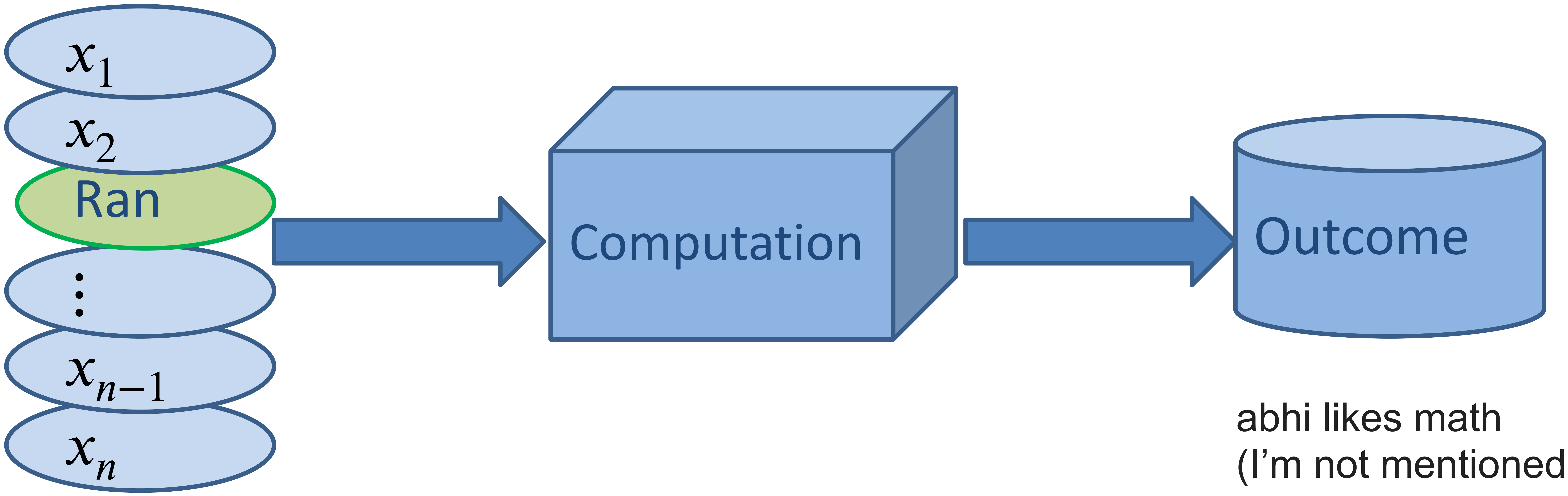
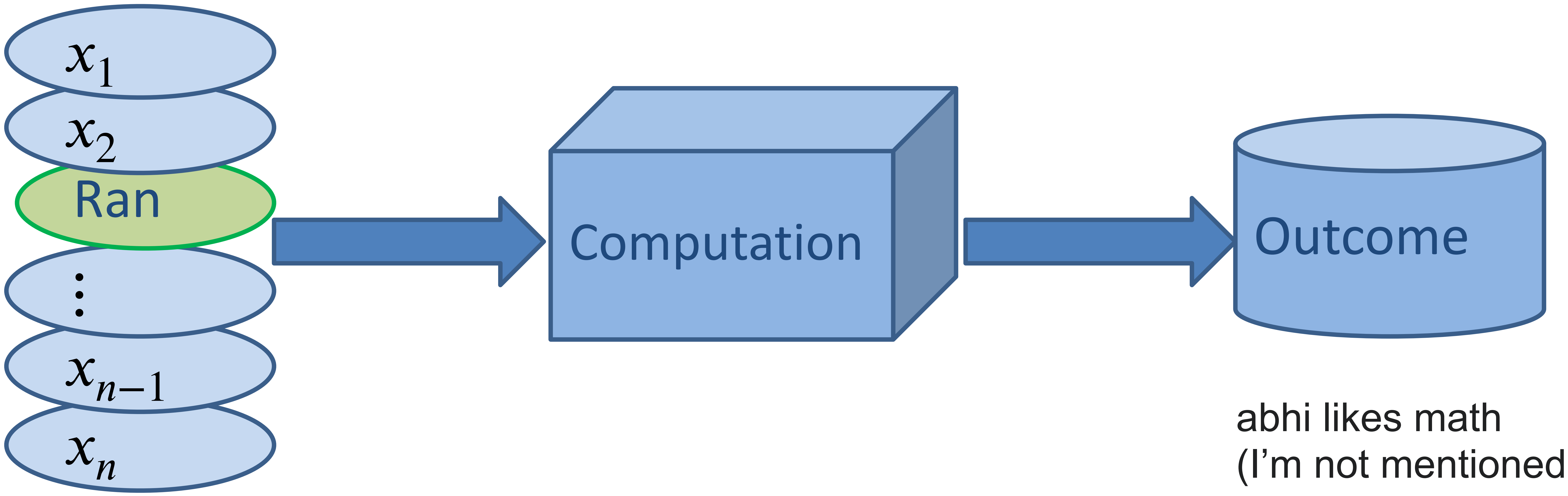


abhi likes math
(I’m not mentioned)

What went wrong?



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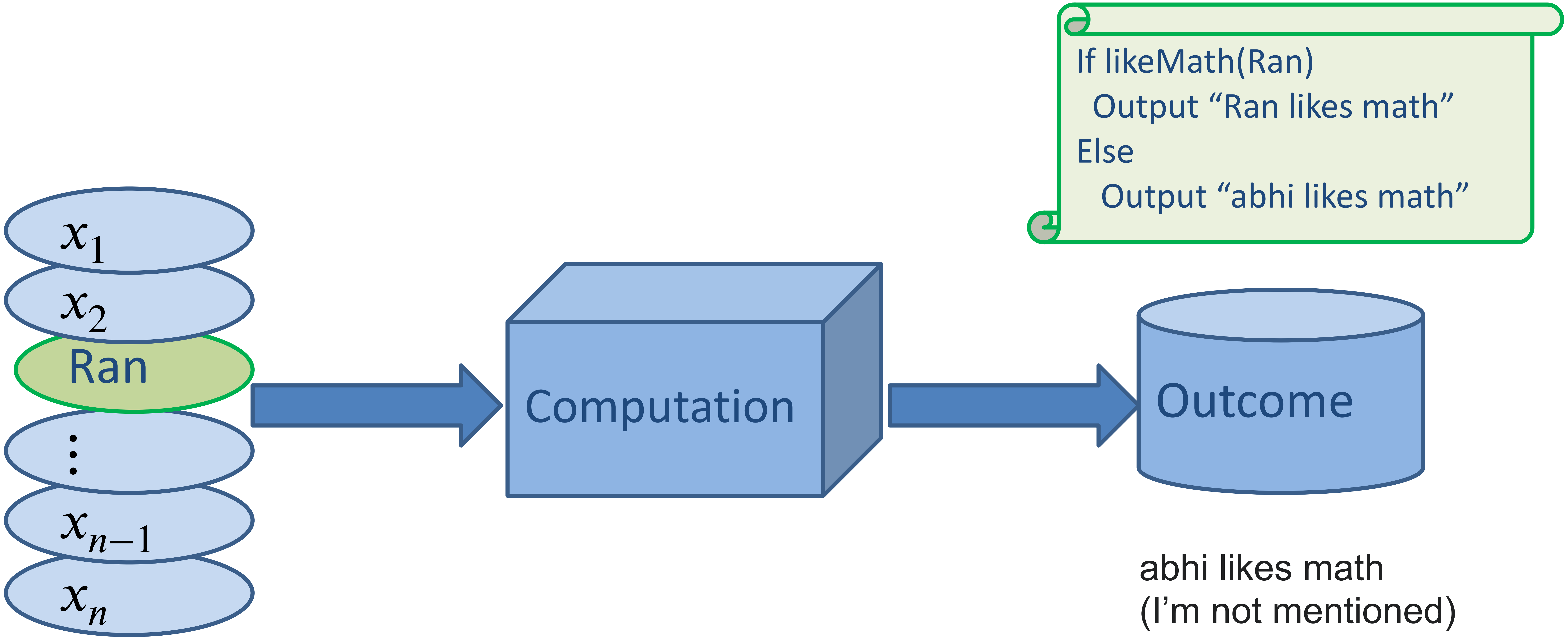

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Privacy analogue

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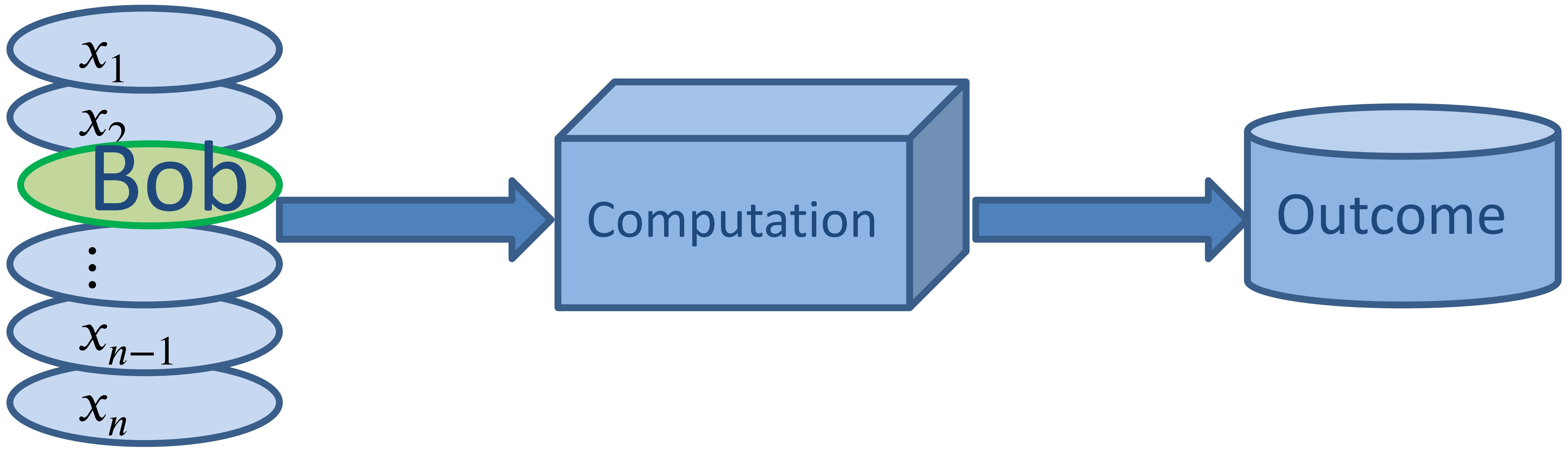
Real world



Privacy analogue

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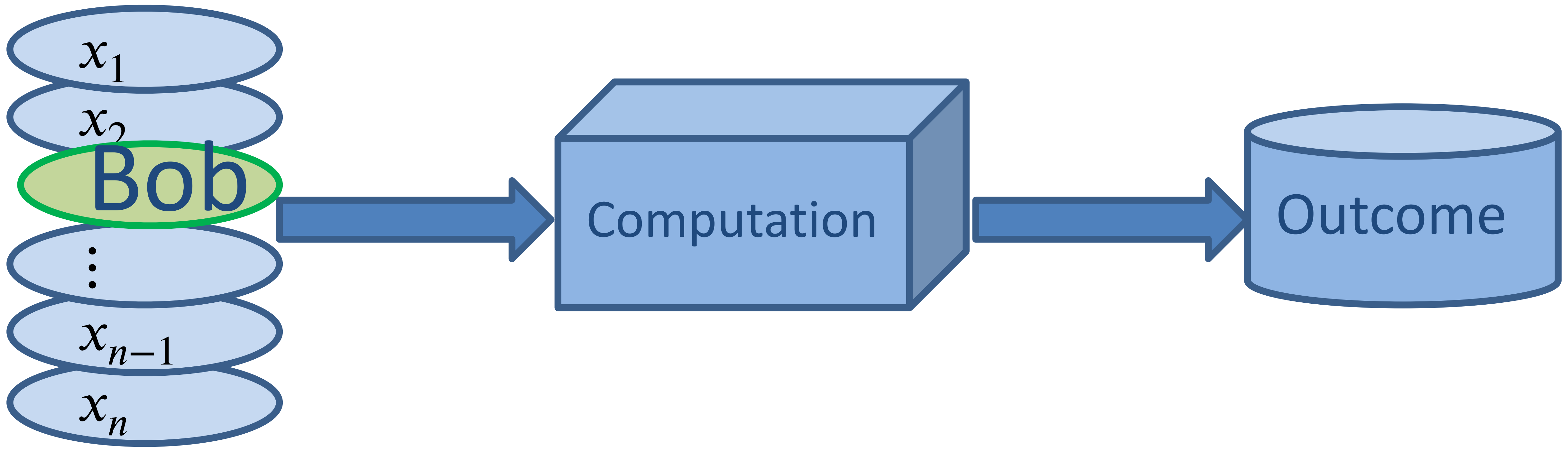
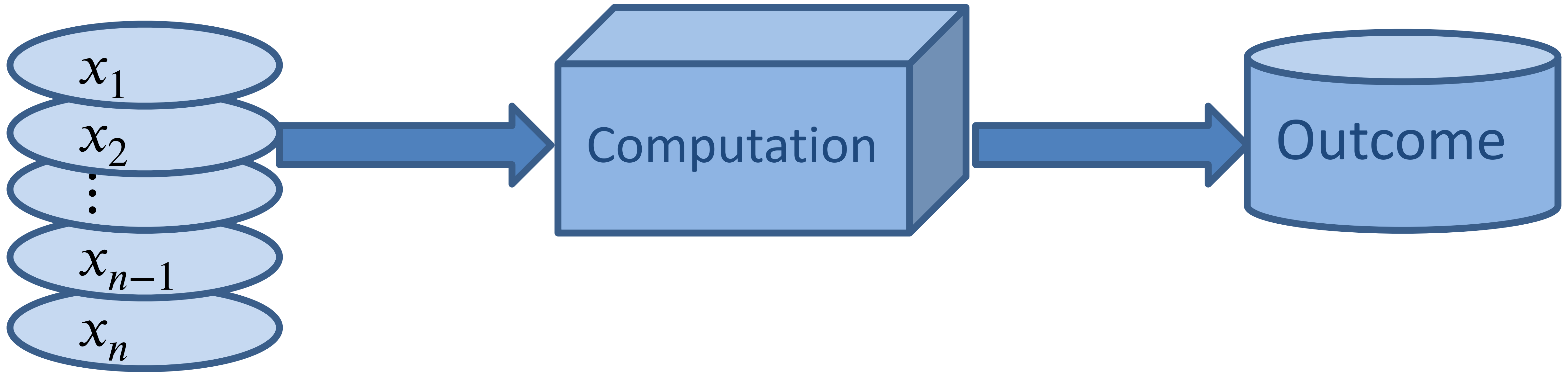


Ideal world



Privacy analogue

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A computation is “private” if whatever can be learned with my record in the DB can be learned without my record

Differential Privacy [Dwork, McSherry, Nissim, Smith 2006]

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A mechanism / algorithm / computation M has **ε-differential privacy** if for any pair of neighboring databased D_1, D_2 (differing by 1 record) and for any $S \subseteq \mathrm{Range}(M)$

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A mechanism / algorithm / computation M has **ε-differential privacy** if for any pair of neighboring databased D_1, D_2 (differing by 1 record) and for any $S \subseteq \text{Range}(M)$

$$\Pr\left[M\left(D_1\right) \in S\right] \leq e^{\varepsilon} \cdot \Pr\left[M\left(D_2\right) \in S\right]$$

Differential Privacy [Dwork, McSherry, Nissim, Smith 2006]

A mechanism / algorithm / computation M has **ε-differential privacy** if for any pair of neighboring databased D_1, D_2 (differing by 1 record) and for any $S \subseteq \mathrm{Range}(M)$

$$\Pr\left[M\left(D_1\right) \in S\right] \leq e^{\varepsilon} \cdot \Pr\left[M\left(D_2\right) \in S\right]$$

Differential Privacy

Adopted by:

- US census Bureau
- Google
- Apple
- YouTube
- Many more